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Investigations on Target Tracking and Classification Using Multiple Sensor Data Fusion

Task II - Survey and Study of Multiple Sensor Data Fusion Architectures and Techniques

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FOREWORD

PARAMAX submits this report as the Task II Report under the provisions of contract number W7701-0-3201/1-XSK.

This document is organized as follows:

EXECUTIVE SUMMARY

TASK II REPORT - SURVEY AND STUDY OF MULTIPLE SENSOR DATA FUSION ARCHITECTURES AND TECHNIQUES

ANNEX A - DATA FUSION LEXICON

LIST OF ACRONYMS

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EXECUTIVE SUMMARY

This Technical Report is presented by PARAMAX Systems Canada (PARAMAX) in response to Services and Supplies Canada (SSC) Contract no. W7701-0-3203/01-XSK for Investigations On Target Tracking and Classification Using Multiple Sensor Data Fusion (MSDF). This report is the second of six to be developed for the MSDF project. The contents of this report fulfil the technical requirements of Task II, "Survey and Study of MSDF Architectures and Techniques", as specified in the PARAMAX Technical Proposal developed in response to Defence Research Establishment Valcartier (DREV) Technical Specification No.1121-90-9.

The goal of Task II is to conduct an exhaustive formal literature survey on the MSDF subject and use the results of the literature survey to conduct performance analyses of the eight sensor data fusion subjects listed below:

1. Sensor Data Association and Fusion Architectures
2. Data Association
3. Data Fusion
4. Data Alignment
5. Target Attribute
6. Application of Artificial Intelligence
7. Target State Estimation
8. Manoeuvre Identification.

The different approaches of analysis published within the surveyed literature are identified for each one of the above subjects, and relative merits and trade-offs between these approaches are analyzed.

The analyses in the Task II report focus on the different approaches in the surveyed literature which could be pertinent to a naval platform employing dissimilar and non-imaging sensors. These analyses establish the knowledge base from which MSDF function implementations for the Anti-Air Warfare (AAW) Frigate will be selected for evaluation in the following tasks of this project.

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TECHNICAL REPORT - Rev. -

TASK II - Survey and Study of Multiple Sensor Data Fusion Architectures and Techniques

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Task II: Survey and Study of MSDF Architectures and Techniques

The objective of this contract is to undertake a study of Multiple Sensor Data Fusion (MSDF) techniques and issues; to analyze, evaluate and propose data fusion algorithms integrating data acquired from dissimilar sensors within the same platform and the Hardware/Software environment supporting these algorithms; and to propose Research and Development topics related to the MSDF domain based on the above analysis.

This study is the second of five analyses performed to accomplish the objective of this contract. It describes the process of the formal literature survey on the MSDF subject, and the results of the analyses of sensor data fusion architectures, techniques and implementations, based on the analyses of the surveyed literature. The analyses focus on the different techniques and approaches which could be pertinent to a naval platform employing dissimilar and non-imaging sensors. The contents of this report respond to the technical requirements of Task II as specified in the PARAMAX Technical Proposal developed in response to DREV Technical Specification No.1121-90-9.

Although this report concludes Task II activities, the literature search and analysis will continue until the end of the project. If other approaches pertinent to the MSDF project are found during the course of the following analyses, they will also be considered when implementations of the MSDF function for the Anti-Air Warfare (AAW) Frigate are being selected (in the following tasks of the project).

This report is divided into the following sections:

1. A Literature Survey
2. An Analysis of MSDF Architectures and Techniques.

The Literature Survey section includes a short description of the process of collecting the literature and describes the Bibliography Database, which includes references of the collected literature and provides quick keyword access to the publications by author, subject, topic, source of publication, year, etc. This detailed description of the database and a listing of all entries pertinent to this MSDF project extracted from the "PARAMAX Research Bibliography Database" document [PARAMAX, 1991] is provided with this report. All literature in this listing was reviewed for the analyses of MSDF Architectures and Techniques, and the most pertinent to each individual technique were selected and referenced within the sections analyzing these techniques. Therefore, the bibliography included in this report is a subset of the literature in the Bibliography Database.

The MSDF Architectures and Techniques Analysis section includes the analysis of the surveyed literature for the eight sensor data fusion subjects listed below:

1. Sensor Data Association and Fusion Architectures
2. Data Association
3. Data Fusion
4. Data Alignment
5. Target Attribute
6. Application of Artificial Intelligence
7. Target State Estimation
8. Manoeuvre Identification.

These analyses constitute the main body of this report. The literature pertinent to each subject is analyzed, the different techniques and approaches are identified, and the relative merits and trade-offs between these approaches are discussed. The analyses also contain mathematical demonstrations, derivations or references for the non-trivial assertions. The simulation results of an approach taken in a study (if available) are also included to enable the reader to observe the trade-offs between the approaches.

Two broad categories of fusion approaches have been discussed in the literature. This report uses [Waltz, 1981] definitions for these categories:

1. Direct Fusion, also referred to as local or autonomous fusion, is defined as the fusion of all sensors on board a single weapons platform.

2. Indirect Fusion, also referred to as global or regional fusion, is defined as the fusion of widely distributed sensors which may look at targets from varying spatial and temporal aspects. This specifically refers to the use of information obtained through the transfer of sensor data involving one or more parties.

This report will mainly concentrate on the Direct Fusion techniques. Indirect Fusion will be discussed only in connection with the analysis of the spatially distributed central-level AAW application of the CL-227 Sea Sentinel Unmanned Air Vehicle (UAV) to augment the sea keeping power of frigate class ships [Szot and Jones, 1991].

II.1 Literature Survey

II.1.1 Introduction

This section describes the formal literature survey performed for the analysis of the MSDF project. The collected literature was categorized and recorded in a bibliography database and a library of this literature was established. During the literature survey, particular effort was made to ensure that all institutions identified by the contract as sources of literature were accessed, and to evaluate if there were any other sources of information pertinent to the project not yet identified. The following paragraphs describe the literature collection process and the bibliography database.

II.1.2 Literature Collection

The survey task started with a visit to the library of the "Ecole Polytechnique de Montréal" which provides high quality systems and services for scientific and engineering bibliographic studies. Many valuable articles on subjects related to data fusion were found and the facility is still being used regularly to update the database.

Contact with the CISTI CAN/OLE II services of the National Research Council of Canada was established through the PARAMAX Data Management Department. Through this service, the American database NTIS and the British database INSPEC were accessed to obtain papers which are not widely distributed.

Through the "Ecole Polytechnique de Montréal" and CISTI CAN/OLE II, many articles were found from the following journals:

1. IEEE Transactions on Aerospace and Electronic Systems
2. IEEE Transactions on Automatic Control
3. The International Journal of Robotic Research
4. Society of Photo-optical Instrumentation Engineer volume
5. IEEE Transaction on Systems, Man, and Cybernetics.

To survey the classified information, the Maritime Warfare Centre of Halifax was visited. Their library was consulted especially for the military classified information about AAW warfare and Command and Control. The DSIS library in Ottawa was also visited and many valuable studies and reports were identified which are available in Canada.

The investigation was not limited to institutional libraries. Trips were also made to meet expert researchers active on data fusion as follows:

- In the Maritime Warfare Centre of Halifax discussions were held with Canadian Navy officers with expertise in fields related to AAW and Target Motion Analysis (TMA).
- In the sonar division of DREA there were discussions with their scientists about the DREA expertise on data fusion systems and techniques.
- The department of electrical engineering of the Royal Military College was also visited where there were valuable discussions with Dr. B. Plant and Dr. M. Farooq about the current status of data fusion technologies and research in Canada.
- A meeting was organized with DNR-3, DMCS-2 and DMCS-7 representatives to learn more about the requirements of the Canadian Navy in the years 2000 and beyond and about any related research within their organizations.
- A trip was also made to meet scientists at DREV who are actively researching data fusion and related subjects.

Another beneficial undertaking of the survey was a visit to Unisys Electronic and Information Systems Group (EISG) in Eagan, Minnesota. There, a technology interchange workshop was held in which different MSDF subjects were discussed and EISG prototype (Fusion Experimental (FX) and ASW Information System (ASWIS)) demonstrations were performed. Other EISG R&D studies, e.g., AN/UYK-44(V) Processor Enhancements (Project 90D203) and Advanced Computer Architecture (Project 89D204), were addressed. However, as these studies are more pertinent to the later stages of the MSDF project (Task IV), most of the time was devoted to the MSDF techniques within FX and ASWIS prototype systems. EISG also provided PARAMAX with unclassified papers from Tri-Service data fusion symposiums for the years 1988, 1989 and 1990.

The Unisys R&D groups in Great Neck, New York and Reston, Virginia were also contacted. It was evaluated that the data fusion related studies performed in these groups are not pertinent to this MSDF project. Great Neck mainly concentrates on target tracking algorithms rather than fusion studies. Reston concentrates on communications, intelligence data fusion, text recognition and tactical situation assessment using expert systems.

When it was evaluated that insufficient information was available about a specific MSDF topic within the surveyed literature, individual experts in different US institutions were contacted. Some examples of literature or explanations received from these experts are given below:

- David L. Hall was contacted at HRB Systems, Inc. in State College, PA, to request the results of his survey of data fusion systems in US published in 1991. This survey is still ongoing, and Paramax will receive the updates to this document.

- Dr. Kuo-Chu Chang was contacted at Advanced Decision Systems in Mountain View, CA, to help clarify some questions about the Multiple Hypothesis Tracking method within the sensor-level architecture. He identified a reference discussing this issue.

- Dr. Samuel S. Blackman was contacted at Hughes Aircraft, Electro-Optical and Data Systems Group in El Segundo, CA, to get his point of view about an implementation of Periodic Establishment fusion method within sensor-level architecture when more than two sensors are fused. He confirmed that the Paramax method could be appropriate at the first sight.

- Dr. Stelios C.A. Thompoulos at the Pensilvania State University in University Park, PA, was contacted to help obtain more literature on data alignment. He was not able to suggest any additional papers on data alignment. However, he sent Paramax two of his studies that he thought could be useful.

- MIT Lincoln Laboratory was contacted to obtain one of their technical notes [Fisher, Muehe and Cameron, 1980], a detailed study of data alignment algorithms for multi-platform systems.

- Dr. John Lowrance at the SRI International Centre for Artificial Intelligence in Menlo Park, CA, was contacted to help obtain more literature in the area of Attribute Association. He sent some background literature to help explain evidential theory, the basis of Attribute Association techniques.

As a result of the above survey, about 250 articles and books that are pertinent to this MSDF project were collected. Some of these are directly referenced within the MSDF Architectures and Techniques Analysis section, some are pertinent to the following tasks of this project and some were used as background information to complement the knowledge base for each MSDF subject.

II.1.3 Bibliography Database

As already explained, the collected literature is recorded in the bibliography database and stored in the data fusion library [PARAMAX, 1991]. This database was developed using DBASE IV software. The records have the following fields: Author, Title, Year, Subject, Source, Type, Classification, Project and Comment. The entries are sorted by Author. The Subject field includes a list of topics that are addressed within the entry. The Source field indicates where the entry was published, and the Type field indicates whether the entry is a book, article, conference presentation, etc. The Project field indicates for which projects the entry is pertinent, and the Comment field contains a short description of the content of the paper.

The collected literature is categorized by the MSDF subject(s) and/or implementations they address. This is indicated in the bibliography database by the included keywords listed below within Subject and/or Comment fields:

Alignment - Data Alignment
Misalignment
Spatial Alignment
Time Alignment

Architecture - Computer Architecture
Distributed Architecture or Processor
Fusion Architecture

Association - Data Association
Joint Probability Data Association or JPDA

Benchmark Algorithm

Coordinates - Polar Coordinates
Cartesian Coordinates

Correlation - Correlated Noise
Time Correlation

Data - Data Alignment
Data Association
Data Fusion

Estimation - Attribute Estimation
State Estimation

Filter - Filtering
Kalman Filter
Adaptive Filter

Human Factor

Intelligence - Artificial Intelligence or AI

Military System or Mission

Multiple Hypothesis Tracking or MHT

Neutral Network

Sensor - Multisensor
Infrared Sensor

System - Expert System

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Target and Tracking - Target Manoeuvre
    Target Model
    Target Tracking
    Tracking Algorithm
    Tracking Multitarget or Multitarget Tracking
    Tracking Target

Theory - Decision Theory
    Evidence Theory
    Bayesian
    Dempster-Shafer
    Fuzzy Logic

As the Title and Comment fields include other data fusion terms that characterize the contents of the study in a more precise way, it is also possible to search for a study using practically any data fusion term pertinent to the MSDF project.

The Subject and Comment fields are continuously refined to provide better access and classification of the literature. This activity will be continuous throughout the life of this project and at the end of each task, the literature used and pertinent for that task will be reviewed and the database updated.

II.2 MSDF Architectures and Techniques Analysis

The collected MSDF literature was studied to qualitatively assess the performance of the following architecture analysis, and fusion and implementation processes:

1. Sensor Data Association and Fusion Architectures
2. Data Association
3. Data Fusion
4. Data Alignment
5. Target Attribute
6. Application of Artificial Intelligence (AI)
7. Target State Estimation
8. Manoeuvre Identification.

For the analysis of each subject, all literature from the survey discussing the topic was reviewed and the most pertinent was selected. The selection criteria were mainly based on the scope of the project, i.e., analysis of MSDF architectures and techniques for dissimilar non-imaging sensors located on an AAW platform. The selected literature was then studied to derive answers and solutions to the issues raised in the contract.

The analysis of each subject in this report is organized to enable the reader to develop an understanding about a subject without having to read the complete report. The section where this is not completely achieved is the Sensor Data Association and Fusion Architectures, where different MSDF techniques and processes specific to the different architectures were discussed without an explanation of their meaning since that is discussed in detail in the appropriate sections. The definition of these terms is given in the Data Fusion Lexicon included in Appendix A of this report.

This Data Fusion Lexicon was developed by selecting terms pertinent to this MSDF project from the Data Fusion Lexicon published by the Data Fusion Subpanel in the proceedings of the 1989 John Hopkins University Symposium, and by adding additional terms used within this report.

The MSDF function can be separated into three processing levels. In the first level, the target state and identification information is estimated; in the second, situation assessment is performed; and in the third, decision aid processing is performed.

The analyses of most of the subjects in this report (Data Association, Data Fusion, Data Alignment, Target Attribute, Target State Estimation and Manoeuvre Identification) address the mathematical models and algorithms within the first level of the MSDF function. Applications of AI are most often found within the second and third levels.

II.2.1 Sensor Data Association and Fusion Architectures Analysis

II.2.1.1 Introduction

Before an MSDF function can be implemented within a combat system, it must be analyzed in terms of what different architectures and implementations are possible, what the benefits and drawbacks of these implementations are and how all this relates to the performance and mission requirements of the platform.

The technological advancement of future threats to the Navy (faster, stealth, etc.) has caused a reevaluation of how sensors should be integrated and their role in the data measurement and decision processes. The surveyed literature addresses different benefits in terms of increasing the processing gain derived in surveillance systems by combining the data and target class declarations using multiple sensors. The performance improvements have been demonstrated on a number of MSDF simulation systems for certain simple applications. Mathematically, as a special case, the use of classical Bayesian estimation techniques [Nahin and Pokoski, 1980] proves that for identical and statistically independent sensors, more sensors improve performance.

Within the surveyed literature, many different ways to combine data from multiple sensors have been found. The term "MSDF architecture" is used to indicate the general method (philosophy) of combining the sensor data. Depending on the way the sensor data is combined, the benefits are different. The combat system performance requirements differ from platform mission to platform mission. Therefore, the selection of the MSDF architecture should be aimed at optimizing the system target detection and tracking performance required for the differing missions of the platform. The selection of the MSDF architecture is also constrained by the hardware and software technological capabilities of the sensor and command and control systems.

The analysis of the different levels at which sensor data is combined into tracks in an MSDF function is summarized from [Alspach, 1983; Reiner, 1985; Blackman, 1986, ch. 13; Chao, Drakopoulos, Lee, 1987; Yannone, 1988; Drummond and Blackman, 1989; Bruder and Farooq, 1990; Krzysztofowicz and Long, 1990; Waltz and Llinas, 1990]. Three types of fusion architectures have been identified, based on the level at which the sensor data is processed:

1. Sensor-level
2. Central-level
3. Hybrid.

The fusion processing within these architectures is referenced as:

a. Sensor-level or track-to-track fusion, distributed or autonomous tracking, shown in Figure II.1 adapted from [Reiner, 1985]

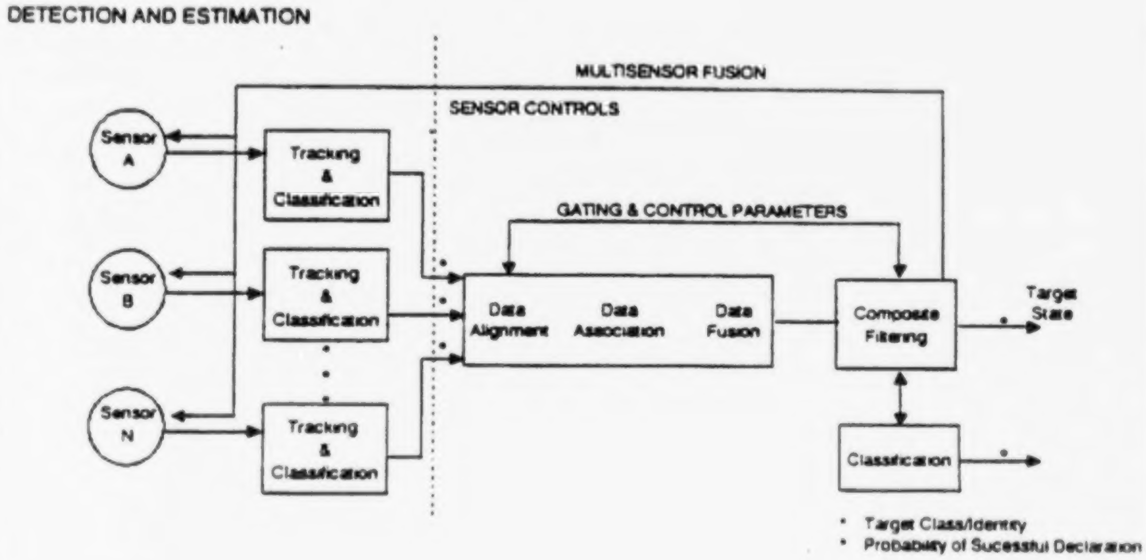
DETECTION AND ESTIMATION
MULTISENSOR FUSION
SENSOR CONTROLS
Sensor A
Sensor B
Sensor N
Tracking & Classification
Tracking & Classification
Tracking & Classification
GATING & CONTROL PARAMETERS
Data Alignment
Data Association
Data Fusion
Composite Filtering
Target State
Classification
• Target Class/Identity
• Probability of Sucessful Declaration

Figure II.1. Sensor-Level Fusion Architecture

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b. Central-level, report-to-track or measurement fusion, centralized tracking, shown in Figure II.2 adapted from [Reiner, 1985]

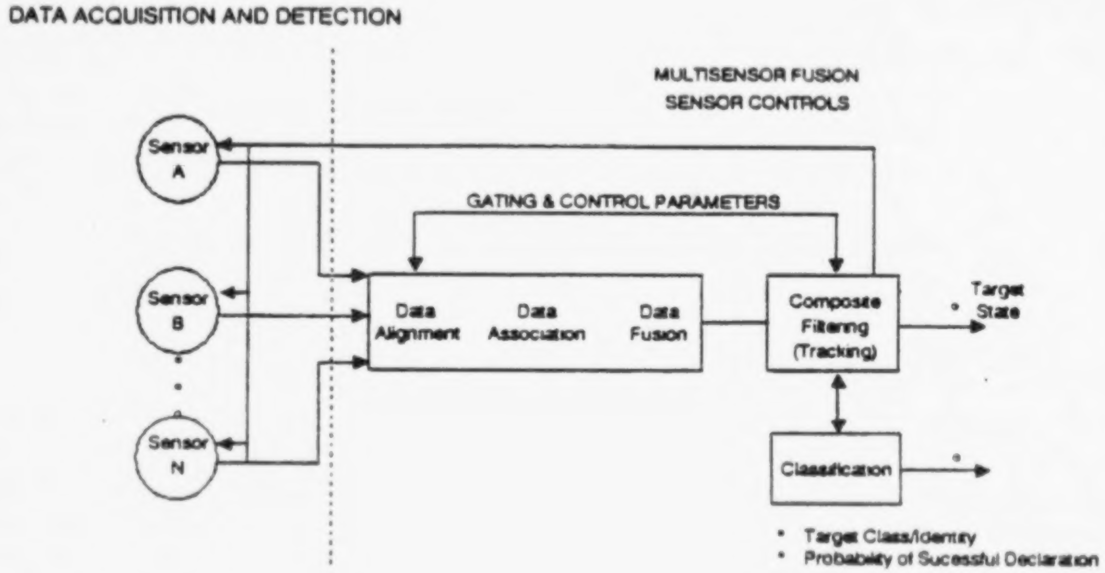
DATA ACQUISITION AND DETECTION
MULTISENSOR FUSION
SENSOR CONTROLS
Sensor A
Sensor B
Sensor N
GATING & CONTROL PARAMETERS
Data Alignment
Data Association
Data Fusion
Composite Filtering (Tracking)
• Target State
Classification
• Target Class/Identity
• Probability of Sucessful Declaration

Figure II.2. Central-Level Fusion Architecture

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c. Hybrid tracking, which is some combination of both sensor- and central-level, shown in Figure II.3, adapted from [Reiner, 1985].

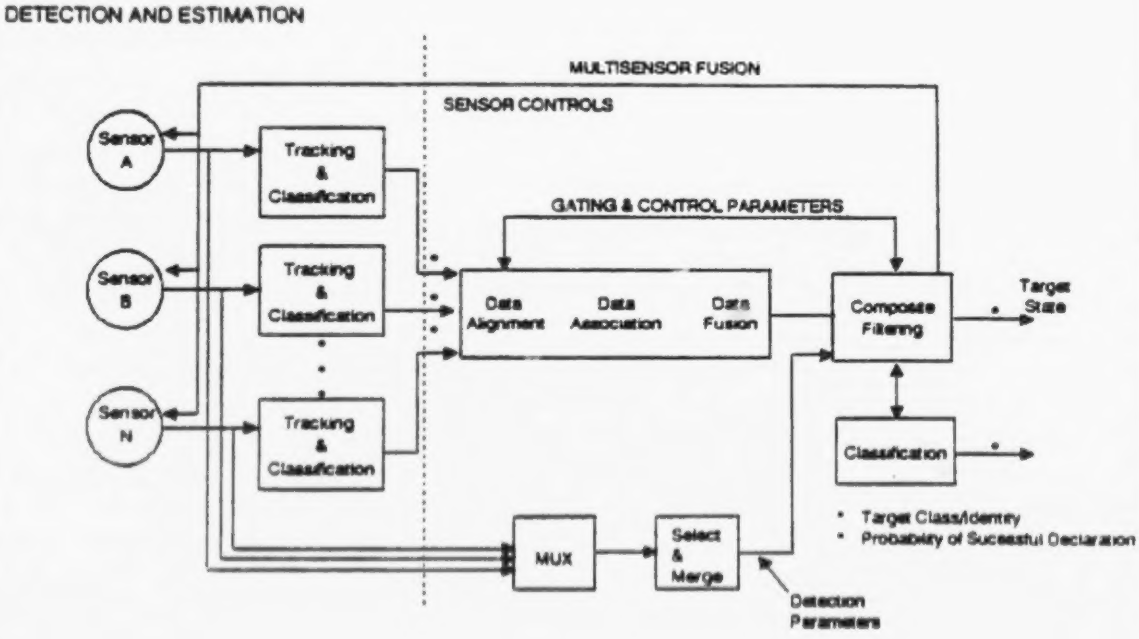
DETECTION AND ESTIMATION
MULTISENSOR FUSION
SENSOR CONTROLS
Sensor A
Sensor B
Sensor N
Tracking & Classification
Tracking & Classification
Tracking & Classification
GATING & CONTROL PARAMETERS
Data Alignment
Data Association
Data Fusion
Composite Filtering
Target State
Classification
Target Class/Identity
Probability of Successful Declaration
MUX
Select & Merge
Detection Parameters

Figure II.3. Hybrid Fusion Architecture

Sensor-level fusion is based on an independent detection and state estimation performed within the signal processor and tracker of each sensor. The tracks in the sensor track files would be established primarily based on measurements received from the individual sensors, but some communication among the sensors and between the sensors and the central file may be used to update sensor-level track files. These sensor-level tracks are then combined into a central track file [Reiner, 1985; Blackman, 1986, ch. 13] by the fusion centre.

The central-level fusion uses the data detected directly from the sensor. Each sensor transmits its observations with negligible delay, through large bandwidth communication links, to the fusion centre where the state estimation and association of the multisensor data are performed to generate composite tracks. Due to the dissimilarity among the various sensor data, the most complex part of this method is the managing of the association function [Reiner, 1985; Blackman, 1986, ch. 13].

The hybrid architecture combines the benefits of both aforementioned methods. It allows data reduction prior to fusion as in the sensor-level fusion while permitting extraction of raw observations as in the central-level fusion to allow for selective enhancement of target declarations and resolution of ambiguities [Reiner, 1985; Blackman, 1986, ch. 13].

In each architecture, the fusion results can be fed back into the sensor subsystems to provide cuing, threshold control, etc., for the purpose of optimizing the overall response [Reiner, 1985].

This section includes a discussion of different fusion architectures found within the surveyed literature, an analysis of the trade-offs between them, and a short discussion of the trade-offs of these architectures onboard the AAW frigate defined in Task I.

II.2.1.2 Sensor-Level Fusion Architectures of the MSDF Function

When using the filtered estimates of the target state vector in the fusion centre, the data association, fusion, and state estimation algorithms within the fusion centre are different from the conventional algorithms used in each sensor since the data being fused in the fusion centre are correlated [Brandstadt, 1988]. The surveyed literature discussing sensor-level architectures concentrates on studying, analyzing and deriving different implementations of the fusion centre algorithms.

There are two fundamentally different methods of integrating data from multiple sensors within sensor-level fusion architecture: fusion with hard-decision sensors (also called hard fusion) and fusion with soft-decision sensors (also called soft fusion).

II.2.1.2.1 Sensor-Level Fusion with Hard-Decision Sensors

Within a sensor-level fusion architecture using hard-decision sensors, decision fusion is performed. Hard-decision sensors measure signals and return yes/no responses (declarations) based upon decision criteria within each sensor. That decision is reported to the fusion centre [Buede and Waltz, 1989]. Mathematically this is expressed as follows [Krzysztofowicz and Long, 1990]:

> For a system of n sensors, each sensor i is connected to its own forecaster $\vec{H}_i$ that maps an observation vector $\vec{Y}_i$ into the detection probability
>
> $$\vec{x}_i = P(\omega = 1 \mid \vec{Y}_i) = \vec{H}_i(\vec{Y}_i) \qquad \text{(II.1)}$$
>
> where $\omega \in \{0,1\}$ is a binary event indicating presence of a signal. This is next mapped by a decider $\vec{D}_i$ into decision $\vec{a}_i = \vec{D}_i(\vec{x}_i)$. The vector $(\vec{a}_1, ..., \vec{a}_n)$ of the binary decisions is input into the fusion rule $\vec{D}$ that prescribes the final decision $\vec{a} = \vec{D}(\vec{a}_1, ..., \vec{a}_n)$.

The implementation of sensor-level architecture using hard-decision sensors for the AAW frigate would entail the following:

1. The track processing algorithms within the long range and medium range radar and the Infra-Red Search and Track (IRST) and Electronic Support Measures (ESM) subsystems analyze the contact data until they have a firm track. Note that this may require contact dat for many scans for each sensor.

2. The track data is provided to the fusion centre which fuses the tracks from the radars, the Identification Friend or Foe (IFF) responses, the IRST and the ESM and obtains a new (more precise) definition of that track.

To optimize the performance of the MSDF function implemented in this way, the decision rules of both, sensors and fusion centre (the $\vec{D}_i$ of the sensors and $\vec{D}$ of the fusion centre) are optimized. Solutions have been proposed for three design situations:

1. In [Tenney and Sandell, 1981] the optimal decision rule of the sensors is obtained when the fusion centre rule is fixed and the local observations are independent, i.e., mathematically, the optimization of the decision rules $\vec{D}_i$ for a fixed fusion rule $\vec{D}$ is performed. This study is limited to the problem of distributed detection with two hypotheses and two sensors.

2. [Chair and Varshney, 1986] optimized the fusion centre rule assuming fixed thresholds for the sensors and independent local decisions, i.e., optimization of the fusion rule $\vec{D}$ for fixed decision rules $\vec{D}_i$ is performed. The combining rule is a function of probability of false alarm and probability of miss of individual detectors, i.e., the reliability of individual detectors.

3. In [Reibman and Nolte, 1987] the fusion centre rule and sensor rules are solved to obtain overall optimal performance, i.e., joint optimization of $\vec{D}, \vec{D}_1, ..., \vec{D}_n$ is performed. With respect to the total system performance, this design is at least as preferred as the other two. However this comes at a price: the joint optimization problem is computationally complex, especially for large n. It becomes tractable when all sensors are characterized by the same likelihood function - the assumption that guarantees an identical decision rule for all sensors - but that is, obviously, very restrictive [Krzysztofowicz and Long, 1990].

There are a number of other analyses of algorithms that are variations of the above situations:

- [Sadjadi, 1986] generalizes the work of [Tenney and Sandell, 1981] to the case of N detectors and M hypotheses.

- [Lauer and Sandell, 1982] consider Bayesian detection of signal waveforms in the presence of noise.

- [Teneketzis, 1982] uses the results of [Tenney and Sandell, 1981] to devise a sequential (quickest) decentralized detection problem.

- [Barkat and Varshney, 1987] develop algorithms for Cell-Averaging Constant False-Alarm Rate (CA CFAR) detection.

No studies which consistently analyzed the implementations of the above methods were found within the surveyed literature. An analysis of these methods as a function of the sensor suite, the performance requirements of the MSDF function and processor resource availability would greatly enhance the comprehension of benefits and drawbacks of different implementations of hard fusion systems. This would be especially beneficial since most of current sensor systems provide binary decisions.

II.2.1.2.2 Sensor-Level Fusion with Soft-Decision Sensors

Within a sensor-level fusion architecture using soft-decision sensors, sensors return a measure of confidence (such as a probability) that quantifies the uncertainty in detection and/or identification. Soft-decision sensors quantitatively "classify" the measured data. They report multiple hypotheses to the fusion centre with a quantitative measure of uncertainty or confidence value for each hypothesis [Buede and Waltz, 1989]. Note that most current sensors do not report multiple hypothesis and the discussions in this paragraph are based on theoretical or simulation analyses. Mathematically this is expressed as follows [Krzysztofowicz and Long, 1990]:

> Each sensor i is coupled with its own forecaster $\vec{H}_i$ that maps an observation vector $\vec{Y}_i$ into the detection probability
>
> $$\vec{x}_1 - P(\omega - 1 \mid \vec{Y}_1) - \vec{H}_1(\vec{Y}_1) \qquad \text{(II.2)}$$

The resultant vector ($\vec{x}_1, \ldots, \vec{x}_n$) of the detection probabilities is input into the fusion rule $\vec{H}$ that outputs the posterior detection probability

$$p = P(\omega = 1 \mid \vec{x}_1, \ldots, \vec{x}_n) = \vec{H}(\vec{H}_1(\vec{Y}_n), \ldots, \vec{H}_n(\vec{Y}_n)) \qquad \text{(II.3)}$$

on the basis of which the detection decision a = A(p) is made.

The implementation of sensor-level architecture using soft-decision sensors for the AAW frigate would entail the following:

1. The track processing algorithms within the long range and medium range radar and the IRST and ESM subsystems analyze the contact data and evaluate probabilities that there could be a track for each contact. This could be done at different levels of granularity. Note that the finer this granularity is the fewer scans will be required to make a decision (because, e.g., contact data from more scans is required to establish a track with 95% probability than with 50% probability).

2. Track data with probabilities are provided to the fusion centre which fuses the probabilities for the tracks from the radars, the IRST and the ESM and obtains a new (more precise) definition of that track. The overall time required to make a decision in this case will be shorter than in the cse of the hard-decision sensors since the sensors provide information about their detections after fewer scans.

Numerous methods have been suggested on how to implement soft-decision sensors. Each is uniquely related to an uncertainty measure and a means of combining the soft decision data into a composite measure [Buede and Waltz, 1989].

The simplest sensor includes multiple decision thresholds (high-medium-low confidence levels) for each hypothesis (H_0 no signal present, H_1 signal present). The resulting output is a vector where each hypothesis is represented by a measure that takes on one of three confidence values [Buede and Waltz, 1989].

A second level of complexity adds multiple hypotheses (H_i). Each has a hard decision rule that determines the hypothesis selected for any given measurement. Parametric data is provided in the form of conditional probabilities which model the behaviour of the sensor, relating the probability of the presence of each hypothesis (e.g., a target class) conditioned upon the decisions that are made by the sensor processor. This category of sensor is called parametric because the parameters contained in the conditional probability matrix (CPM) must be known before the operational sensing of the environment in order to describe the sensor's performance for any given decision. In order to develop CPM, the probability density functions (PDFs) for each possible target class (hypothesis) must be known [Buede and Waltz, 1989].

The use of a nonparametric statistical pattern recognition algorithm provides a high level of softness in the sensor. The algorithm quantifies, for each individual measurement, the uncertainty as a measure of the statistical distance between the sensed measurement and a representation of the signal expected for each hypothesis. Naturally, the form of uncertainty that is output by the sensor must be directly related to the choice of fusion approach [Buede and Waltz, 1989].

In the surveyed literature different methods of implementing or evaluating the implementation of soft-decision sensors were found. Each study only evaluates a limited application (a special case) and includes some trade-off analysis for the selected implementation. There are also some studies where the fusion centre receives mixed reports from soft-decision sensors, hard-decision sensors or raw data. These studies are important in developing a qualitative understanding of different sensor-level architecture implementations. This will be especially useful during the analysis in Task III. Examples of such systems are given below.

II.2.1.2.3 Examples of Sensor-Level Fusion Implementations

1. [Bowman, 1979] develops a multisensor integration (MSI) track filtering algorithm for defensive fire control surveillance. This algorithm is also discussed in [Bowman and Morefield, 1980] and [Bowman and Gross, 1985]. The MSI algorithm is sequential in time and by sensors. The MSI simulation effort concentrates on optimizing the manner in which the sensor track file generation filtering schemes affect MSI performance, the behaviour of MSI track correlation, and filtering algorithms under a variety of conditions. [Bowman and Gross, 1985] report improved performance for their approach (sequential by time and sensor) compared with the sequential by report approach.

2. [Chong, Chang and Mori, 1986] and [Chong, Miltonberger, et al, 1984] discuss a distributed sensor network (DSN) made up of a set of nodes which can communicate with each other via a communication network. Each DSN node contains a processor which collects data from certain sensors. The processor performs tracking functions using the local sensor data and communicates the processing results to other nodes according to a communication strategy. This approach retains multiple data-association hypotheses when the situation is unclear as to which measurements originate from which targets. The multiple hypotheses are then processed with

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the new data. Simulation results show that the tracking improves as communication between nodes is increased. Also the multiple hypotheses are beneficial when data quality is poor. These systems are classified within sensor-level fusion architectures. However, within each node, both track-to-track fusion and report-to-track fusion is performed. They could also be classified within hybrid architecture.

3. A similar distributed system is discussed by [Fahmy and Titus, 1987] - a DSN which they call Horizontal Estimation Architecture (HEA). The term "horizontal" is used to imply that the geographically dispersed nodes do not differ in rank. In HEA, each node in a DSN only performs local processing of the data collected by its own sensor/sensors. The locally processed data from each node are communicated to neighbouring nodes, providing a mesh network topology. The HEA can be further extended to cover a very large scale DSN in the case where each node can be the central processor of a centralized network or a global processor of a hierarchical network.

4. [Chang, Chong, Bar-Shalom, 1986] derive the Joint Probabilistic Data Association (JPDA) algorithms for sensor-level architecture. (Note that JPDA is one of the common approaches specific to central-level architecture). In this approach, each sensor processes the local sensor measurements and sends the local estimates periodically to the fusion centre. After processing the results, the fusion centre sends back the global estimates to each sensor. These algorithms were simulated for a two sensor scenario. Three communication schemes were examined: (a) decentralized - no communication between sensors, (b) centralized - all sensors send measurements to a fusion centre, (c) distributed - two sensors interchange information every five scans. The centralized scheme performs the best, the decentralized scheme performs the worse, and the distributed scheme performs reasonably well. To evaluate impact and communication costs, different communication rates were simulated. The results show that the distributed scheme performs reasonably well when the two nodes communicate every five scans. This study also points out that in some cases, to increase reliability the algorithm may require less communication than transmission of all measurements, e.g., high clutter density.

5. [Chao, Drakopoulos and Lee, 1987] discuss a distributed detection system where each local detector sends a "subset" of M candidate hypothesis and a discrete confidence level for each hypothesis to the fusion centre. In the fusion centre the local decisions are combined using Dempster-Shafer theory. The performance of two such algorithms (using different decision rules) is evaluated in special cases (three hypothesis and two or five local sensors) and is compared with a hard decision system. Both multihypothesis algorithms outperform the hard decision system and the case with more sensors has lower probability of error.

6. [Brandstadt, 1988] compares the measurement fusion (soft fusion) and track file fusion (hard fusion) algorithms in the case of two tracks and two sensors. The simulation of the two

algorithms shows that the first has the better performance. However, if the second must be used, the cross covariance term between the sensor's kinematic state vector estimates can be ignored.

7. [Feldman, 1988] analyzes the data fusion requirements of the U.S. Navy's Advanced Combat Direction System (ACDS) Block 1 track management function. This system must fuse data from a variety of sources, some in the form of raw data and some processed tracks. Trade-off studies for choices for threshold values and filter gain, etc. are performed. It is determined that Block 1 quantitative requirements for dual designations and false correlations for tracked objects could be met through this scheme if tracks being compared had unbiased position estimates and reasonably accurate covariance data where available. Since most of the trackers that interface with Block 1 are not designed to provide covariance data, Block 1 contains algorithms for estimating covariances. Also, in this system the operator tunes the correlation and identification algorithms. The effect of these controls is to modify thresholds and filter gains and the declaration thresholds.

8. The probabilistic approach is implemented for the simulation by [Buede and Waltz, 1989] and [Buede, Martin and Sipos, 1989]. Probabilistic algorithms are used for state estimation and AI is used for attribute estimation. A soft sensor suite with Bayesian fusion is shown to provide a 30 percent increase in range at identification (since the fusion centre receives the probabilistic data sooner than if it had to wait until the sensor acquires a firm track).

9. [Klein and Kassis, 1989] describe a distributed data fusion system which performs soft fusion (sensor systems provide data with confidence levels). The fusion centre algorithm processes mixed data measurements and tracks and performs sensor cuing (e.g., changes sensor threshold, provides locations of selected targets, etc.). The paper identifies the need for better algorithms, faster computational processing, parallel processing, etc.

10. [Lee and Chao, 1989] discuss a distributed data fusion system where each local detector provides the fusion centre with multiple-bit detection which represents its decision and, conceptually, its degree of confidence on that decision. Only one-way communication is assumed between each sensor and the fusion centre. They show that the proposed system significantly outperforms the one in which each sensor provides only a hard decision. They also show that based on optimum sub-partitioning of local decision space, the detection performance increases monotonously with the number of partitions. Furthermore, it is shown with a numerical example that the distributed system using 2-bit local decisions significantly outperforms the one using one-bit hard local decisions and is not far from the optimum centralized system.

11. [Bruder and Farooq, 1990] list different fusion techniques for the sensor-level architecture. They report that the almost exclusive use of hard fusion techniques to perform track-to-track fusion

results in a corresponding slight decrease in tracking accuracy. Soft fusion techniques such as the decentralized information type fusion technique can be utilized to remedy the shortcoming.

II.2.1.2.4 Architecture Analysis of Sensor-Level Fusion

As is evident in the above mentioned analyses, system performance improves with soft-decision sensors. [Krzysztofowicz and Long, 1990] include an analytical comparison of the performance of sensor-level fusion using hard and soft-decision sensors with the performance of central-level fusion. They show that the Bayes risk (cost of making the wrong decision) for fusion with soft-decision sensors is never larger than for fusion with hard-decision sensors and it is never smaller than for centralized fusion system. They are equal if for every i = 1, ..., n, the probability $\vec{x}_i=\vec{H}_i(\vec{Y}_i)$ constitutes a sufficient statistics of observation $\vec{Y}_i$ with respect to $\vec{F}$, so that

$$\vec{H}(\vec{H}_1(\vec{Y}_n), \ldots, \vec{H}_n(\vec{Y}_n)) - \vec{F}(\vec{Y}_1, \ldots, \vec{Y}_n) \tag{II.4}$$

[Buede and Waltz, 1989] explain that the prime criteria for deciding whether soft-decision sensor architectures provide any benefit over hard-decision sensor approaches is as follows: the regions (in time, space or signal level) of signal measurements by different sensors must overlap as they transition from zero to maximum value; the greater the overlap, the larger the performance improvement that can be expected.

The soft fusion method falls between centralized and hard fusion methods not only in terms of the Bayes risk, but also in terms of the complexity of information that must be communicated by individual sensors to the fusion centre: it is a real number $\vec{x}_i$ versus an observation vector $\vec{Y}_i$, or a binary number $\vec{a}_i$. The resultant differences in requirements for communication channel bandwidth of electronic systems may be significant. Flexibility of the system may be of import in some applications, and in this respect, the soft fusion method offers two attractive features. First, any replacement, addition, or deletion of individual sensors in the soft fusion method requires only the re-estimation of the probability fusion rule $\vec{H}$ in the fusion centre to ensure optimal performance of the reconfigured system. The same modification in the hard fusion method requires re-estimation of both the decision fusion rule $\vec{D}$ in the fusion centre and the decision rules $\vec{D}_1,\ldots,\vec{D}_n$ in all sensors of the reconfigured system. Second, the forecasters $\vec{H}_1,\ldots,\vec{H}_n$ in the soft fusion method can be of any type and need not be structurally isomorphic. All forecasters in the hard fusion method must be of the same type; they must be explicit Bayesian processors (or likelihood ratio processors) of observations [Krzysztofowicz and Long, 1990].

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The different algorithms and approaches discussed in the surveyed literature (paragraph II.2.1.2.3) can be classified into two groups:

1. There is no communication between the sensor systems, and only one-way communication between the sensor systems and the fusion centre [Bowman, 1979; Chao, Drakopoulos and Lee, 1987; Brandstad, 1988; Feldman, 1988; Buede and Waltz, 1989; Klein and Kassis, 1989; Lee and Chao, 1989; Bruder and Farooq, 1990],

2. There is two-way communication between sensor systems and with the fusion centre (when applicable) [Chong, Miltonberger et al, 1984; Fahmy and Titus, 1987; Chang, Chong and Bar-Shalom, 1986; Chong, Chang and Mori, 1986].

In the second case, the trade-off is improved performance and higher flexibility versus increased communication requirements.

In the studies discussed above it is also established that methods that fuse probabilities, (i.e., report and combine multiple hypothesis with uncertain data) require (1) significantly more processing capability (than in the hard fusion method), and (2) higher database requirements (than in the hard fusion method), especially if a multiple hypothesis method is selected.

The benefits of the soft fusion method are (1) higher tracking performance and increased range of detection, (2) high flexibility, (3) modest (compared to central-level fusion) requirements for communication channels, and (4) a suitability in situations wherein observations are naturally in the form of detection probabilities. Since in this method the sensors report probabilities before a target is firm, there will be more time to process any given target and potentially multiple tracks with the same target [Chong, Miltonberger, et al, 1984; Buede and Waltz, 1989; Krzysztofowicz and Long, 1990].

In conclusion, compared with the hard fusion method, the soft fusion method, with an appropriate fusion algorithm, will provide tracking performance improvements both in time and range, but at the expense of increased communication, computational and database requirements.

II.2.1.3 Central-Level Fusion Architecture of the MSDF Function

Within a central-level fusion system, fusion of observations (or measurements) is performed. All reported data is sent directly to a fusion centre where a master track file is maintained. Mathematically the central-level fusion is expressed as follows [Krzysztofowicz and Long, 1990]:

Each sensor I supplied an observation vector $\mathbf{Y}_i$ to a central forecaster $\vec{F}$ that outputs the detection probability

$$q = P(\omega = 1 \mid \vec{s}_1, \ldots, \vec{s}_n) = \vec{F}(\vec{s}_1, \ldots, \vec{s}_n) \tag{II.5}$$

on the basis of which a decider A prescribes decision a = A(q). This is the classical algorithm for establishing a detection decision in a single sensor, sometimes referred to as the "fusion for a single sensor".

The implementation of central-level architecture for the AAW frigate would entail the following:

1. No track processing is required within the long range and medium range radar and the IRST and ESM subsystems to analyze the contact data.
2. The contact data are provided to the fusion centre which fuses contacts from the radars, the IFF, the IRST and the ESM and obtains precise definition of tracks. Since the fusion contre does not wait until the contact information is obtained, the overall time required to make a decision about a track is shorter than in the case of sensor-level architectures.

Within the surveyed literature the following observations were made about the benefits of central-level fusion:

1. Tracking accuracy is maximized. Probability of misassociation is decreased [Reiner, 1985; Drummond and Blackman, 1989; Bruder and Farooq, 1990],
2. Fusing the measurements at each sampling time and running a single centralized filter yields smaller state estimation errors than with data obtained by fusing the two decentralized estimates by about 6-8 percent [Bar-Shalom, 1988],

and the drawbacks of central-level fusion:

1. The centralized approach requires backup processing and track files for survivability in case the platform (or platforms) containing the central track file fails [Drummond and Blackman, 1989].
2. This is the most complex in terms of communications and computation resources [Alspach, 1983; Tenney and Sandell, 1981; Chao, Drakopoulos and Lee, 1987].

3. This method is not practical because of reliability and survivability [Tenney and Sandell, 1981; Chao, Drakopoulos and Lee, 1987].

4. The fact that parameter accuracy improvements obtained as a result of multisensor fusion are generally less important than the reliability of target class declarations, coupled with the fact that the indicated accuracy performance can be obtained only if the target states are unambiguous (an impossibility in heavy cluster or dense target environment) make this method less desirable than the other methods [Reiner, 1985].

5. Because of such considerations as cost, reliability, survivability, communication bandwidth, compartmentalization, sensors on platforms under emission control, or even simply the problem of flooding the fusion centre with more information than it can process, there is never total centralization of information in practice [Tenney and Sandell, 1981].

In spite of the above mentioned difficulties, there are some studies that attempt to implement the central-level fusion architecture, trying to benefit from improved performance while using different techniques to overcome the five drawbacks enumerated above. These studies are very useful for understanding the differences between the MSDF processes in central-level and sensor-level architectures. With technological advancements in the area of processor and communication resources, most of the above drawbacks will disappear. Until then these studies are also useful for understanding the methods and feasibility of overcoming the aforementioned drawbacks. A brief description of some of these studies is given below.

II.2.1.3.1 Examples of Central-Level Fusion Implementations

1. [Bernardin and Lin, 1988] describe a simulator that has central-level fusion architecture. The simulation sensor suite consists of a radar with three passive sensors, and for the study an attempt was made to obtain sensor reports as close as possible to operational realities. Sensor integration is considered in terms of fusing two- and three- dimensional spacial measurements. This system performs a separate bearing tracking, then fuses with range (radar) measurement data. Four false alarm reduction algorithms were considered for the fusion system: Shafer-Dempster, joint statistical detection (e.g., Bayesian), Pd/Pf ratio (Pd=probability of detection, Pf=probability of false alarm), and M-or-more detection. Based on performance and processing capabilities, the last approach was chosen since it provides a simple solution when noise is uncorrelated across sensors. The results of this multi-sensor tracker simulation show, on the average, 57% position error reduction when a manoeuvring helicopter is being tracked and 40% when a fixed wing aircraft is being tracked.

2. [Hafner, Sutherlin and Thompson, 1988] describe the Naval Command and Control System - Afloat (NCCS(A)) system. Its Afloat Correlation System (ACS) function consists of centralized, parallel processing components which deal with data correlation and information fusion. Within this system the similar source sensor data is collected, correlated and disseminated on standard NTDS communication media in parallel. These dissimilar source tracks and parametric data are fused by a separate function. Thus the ACS function, as incorporated in the integrated NCCS(A) design, centralizes processor intensive data function and track correlation processes (Sensor I/O, Sensor Control, Data Fusion) and distributes the management activities of situation assessment, planning and control.

3. [Easthope, Goodchild and Rhodes, 1989] describe a method that employs an object-oriented system architecture to partition the task in a way that exploits the inherent parallelism to the maximum. The approach involves the allocation of independent synchronous logical processes to track individual targets on a one-to-one basis. The tracking processes each contain identical track initiation, data correlation and tracking algorithms, and are entirely independent of each other. Incoming sensor data is assessed by all tracking processes independently and concurrently for reference to their target tracks, and, if applicable, is then used to update their tracks.

   An important feature of this target-oriented architecture is that system growth is easily achieved by straightforward replication of the individual tracking processes. The architecture has been extended so that clusters of targets, the members of which may or may not be individually resolvable, can be tracked as well as individuals. The overall architecture would be broadly similar for all applications, but embedded algorithms and functions would be tailored to suit each particular case. The system incorporates additional independent processes to route the data efficiently to Object Processes and to collect the output of these processes to form the fused picture of the environment.

   This system can process either measurement or track data. Its performance is evaluated for input data in any of the following forms:

   - individual, uncorrelated sensor plots or bearing-only "hits"
   - unfiltered scan-to-scan correlated plots or "hits", with the sensor track reference the connection link from one report to the next
   - fully correlated and filtered single sensor or multi-sensor tracks.

   The most useful form is that of scan-to-scan sensor plots, which preserve full detail of sensor measurements to the benefit of the fusion/tracking performance while minimizing the data handling within the system. Individual uncorrelated plots also preserve the full measurement detail, but with the penalty of a far higher internal communications load within the data fusion system. Pre-filtered single sensor tracks generally produce less precise multi-sensor tracking due to loss of measurement detail in the single-sensor track filtering

3. [Helbren and Lee, 1980] discuss an approach referred to as combined sensing. This is fundamentally different from that approach adopted when outputs from different sensors are brought together at the pre-processing or detection stages. The sensor suite includes a radar, an Electro-Optic (EO) sensor and an ESM sensor. Although it may be desirable to have all three types of sensors working together, in this situation a particular combination was chosen to provide the most effective solution for the task required on the grounds of processing cost. The hardware and software is designed to operate at the fastest sensor frame rate, as high as the 25 Hz video rate of the EO sensors. The multiple sensor, multiple option plot association and track generation algorithm called Alternative Tracks Method (ATM) maintains a number of track hypotheses scored according to how well the plot data associate with the track, taking into account the computed track accuracy and the assumed accuracy of the sensor from which the data are obtained.

   One important aspect of combined sensing is the effectiveness of the interfaces between the sensor hardware and the computer system performing the integrated track maintenance (improved interfaces are being designed). Although full surveillance data is not available, the integrated system can direct a window on to any target which needs to be updated. Limited area surveillance is possible and any number of interfaces can be connected to one or more radars.

4. [Allen, Kurien and Washburn, 1986; and Cybenko, Allen, 1987] describe algorithms for doing central-level fusion using parallel computer processing. [Allen, Kurien and Washburn, 1986] use a track-oriented approach, while [Cybenko and Allen, 1987] break the tracking space into multidimensional binary partitions (MBP), which are volumes of tracking space which have, approximately, an equal number of tracks. In both cases appropriate gating, thresholding, tracking, clustering, re-initializing, etc. algorithms are developed.

5. The Unisys developed FX and ASWIS systems [Unisys, 1991A; Unisys, 1991B; Unisys, 1990] can be also classified as central-level. Both are simulation systems developed for ASW tracking using the multiple hypothesis method. These systems are used to perform algorithm development, algorithm optimization and man-machine interface analysis rather than to evaluate trade-offs of different fusion architectures. Among the issues of concern are issues such as clustering, merging, pruning, etc. FX concentrates mainly on state and attribute evaluation (level 1 fusion) and measure of effectiveness (MOE) analysis of a fusion algorithm, while ASWIS also includes situation assessment process analysis (level 1 and 2 fusion).

II.2.1.3.2 Architecture Analysis of Central-Level Fusion

From the above descriptions, it is clear that to benefit from the performance, accuracy and time advantages of central-level architectures, methods must be found to reduce the communication and processing requirements of the central-level fusion system within a platform.

[Bernardin and Lin, 1988] have achieved this by grouping similar types of sensor report processing and by selecting a less computationally demanding association algorithm (M-or-more). [Hafner, Sutherlin and Thompson, 1988] also grouped similar sensor reports. [Easthope, Goodchild and Rhodes, 1989] developed object-oriented (track and cluster processing) algorithms in order to perform parallel processing. [Helbren and Lee, 1980] limit fusion system capability by only tracking with two sensors and concentrating on sector processing, and finally [Allen, Kurien and Washburn, 1986; Cybenko and Allen, 1987] develop algorithms (conceptually similar to those of [Easthope, Goodchild and Rhodes, 1989]) to take advantage of parallel processors.

The surveyed literature does not quantitatively address the database requirements for the fusion centre of any of the above mentioned systems. The only thing repeated in the literature discussed above is that the database requirements for each target are higher for central-level fusion architecture than for sensor-level fusion architecture. The database requirements also depend on the algorithms selected for different MSDF processes within each architecture. For example the database requirements are higher for the multiple hypothesis method. If the platform also performs level 2 and 3 fusion, which are mainly implemented in AI applications, there will be additional database requirements to support these functions. However, these requirements will be independent of the fusion architecture selected.

None of the above mentioned central-level architectures address the impact on system performance of communication between sensors or between the fusion centre and the sensors.

[Alspach, 1983] suggests that sensor controllability can be made use of, it may be possible to either create a far better picture with limited computation and sensor resources or to greatly reduce the sensor and communications resources required for a given quality of surveillance product. Both analytically and in terms of system architecture this is a complex problem. Optimal sensor control algorithms are computationally intensive. Also, sensors under feedback control produce a data stream that varies in volume and composition according to the current threat situation. This presents more difficult communications and database management problems than do static systems.

In summary, although the central-level architectures are better understood theoretically, considerably fewer practical studies have been performed as compared to those performed for sensor-level architectures. This can be attributed to the fact that computer resources existing at the time of these studies were judged inadequate to support central-level architectures and most sensor systems were not equipped to provide raw data.

The technological advancements in modern threat and threat of the future require higher performance and it is anticipated that future sensor data fusion studies will concentrate more on the area of central-level fusion architectures and the sensors and the computer resources required to support such systems. One of the important issues within these systems to address is the communication between sensors and between the central processor and the sensors. This could be one of the most effective means to reduce the communication and processing load of a central-level MSDF function.

II.2.1.4 Trade-offs Between Sensor-Level and Central-Level Architectures

The paragraphs above included examples of analyses of different fusion architectures, performed theoretically or on a simulation system, aimed at evaluating the feasibility and trade-off for using different sensor-level and central-level fusion architectures.

Points in favour of the sensor-level fusion are [Blackman, 1986, ch. 13]:

1. Reduced data rate or data bus loading
2. Reduced computational loading (in the fusion centre)
3. Enhanced system reliability due to simplified computational complexity of the fusion centre
4. Higher survivability due to distributed tracking capabilities
5. Independence among sensors which insure that if one sensor becomes degraded, its observations will not affect the sensor-level tracks of other sensors
6. The use of sensor-level tracking, allowing design of filter specifically tailored to the individual sensors.

If sensor level tracks are maintained, they must be combined at some point to derive significant benefit from the multi-sensor data fusion approach. The result is central-level tracks updated with sensor-level track data instead of sensor report data. Several problems arise [Blackman, 1986, ch. 13]:

1. If a central-level track is updated with a sensor-level track, the assumption of error independence from one update period to another is not valid. This can be taken into account in the processing, but it forces additional complexity.

2. Less accurate tracking and correlation can be expected if independent sensor-level tracks are maintained. For example, there will be a higher probability of false correlation in areas affected by clutter because the gate sizes in the association process will be larger due to less frequent track updates.

3. If the multiple hypothesis tracking approach is taken in the fusion centre, it would be desirable that this approach be taken not only when sensor-level tracks are combined, but at the sensor-level as well. However, the maintenance of a single hypothesis tree at the fusion centre is simpler than the maintenance of many hypotheses at each sensor as well as additional hypotheses at the fusion centre to combine the sensor-level tracks.

Points in favour of central-level fusion are [Blackman, 1986, ch. 13]:

1. The central-level fusion architecture is evaluated to be the most accurate by all studies reviewed above which analyzed both sensor-level and central-level fusion architectures.

2. Target tracks consisting of observations from more than one sensor should be more accurate than the tracks which could be established on the partial data received by the individual sensors. Thus, the centralized tracking approach should lead to fewer miscorrelations.

3. By processing sensor reports directly, the difficulties (taking sensor cross-correlation into account) associated with combining sensor-level tracks are avoided.

4. Track confirmation and continuity should be improved with central-level tracking and various sensors can be used synergically.

5. The approach whereby all data are sent directly to the central processor should, in principle, lead to faster, more efficient computation (i.e., increased detection and identification range).

There can, however, be a major drawback if pure centralized tracking is used. This problem occurs when the data from one sensor becomes degraded (and this degradation not immediately sensed) resulting in poor central-level tracking [Blackman, 1986, ch. 13].

The associated processing algorithms of central-level fusion are based on the classical theory of single sensor tracking. Although this method is optimal in the detection theory sense, most studies reviewed suggest that it is impractical because of considerations as such cost, timeliness, reliability, survivability and communication bandwidth. Therefore, as previously mentioned, the studies reviewed concentrate on different ways to optimize the sensor-level fusion architecture algorithms and implementations to improve the tracking accuracy while trying to minimize the computational speed and complexity, database size, and communication rate.

Hence, the trade-off between sensor-level and central-level fusion is basically one between decreased transfer load, the computational advantages of parallel processing, and decreased vulnerability, on the one hand, and the possible introduction of intermediate errors on the other [Blackman, 1986, ch. 13] versus increased computational and communication costs on one hand, and faster detection and identification and higher quality track on the other.

II.2.1.5 Particular Strengths and Weaknesses of Hybrid Architectures

The Hybrid architectures are intended to benefit from the advantages of both sensor-level architecture fusion (e.g., lower data bus bandwidth requirements) and central-level fusion architectures (e.g., availability of raw measurements for correlation ambiguity resolution) [Llinas, Hall and Waltz, 1989]. Different variations of hybrid architectures have been suggested in the surveyed literature:

1. [Alspach, 1983] describes a track-to-track fusion strategy using sensor reports (hybrid); data from each sensor is tracked, smoothed, and filtered to create a track of the appropriate target. Then, the tracks from various sensors are correlated at the track level. Instead of simply combining correlated tracks to create a common master track, the system goes back to the individual sensor level, retrieves the sensor data that caused the formation of each correlated track, and processes the data in an extended Kalman filter to produce a fused master track. This method ensures improved surveillance picture.

2. [Blackman, 1986] suggests different hybrid approaches which are intermediary between sensor- and central-level fusion. One technique is to form a central-level track from one of the sensors and then to allow selected measurements from all sensors update that central track. Another method is to average all observations for a given time interval from a given target and use the average for update of the central track.

   The fusion centre would maintain a central-level track file formed using the raw observations in addition to sensor-level tracks as "backup". Consistency checks between the central- and sensor-level tracks could be performed to detect possible sensor degradation. This technique would optimize performance, but the computational and data transfer requirements would be very high.

3. [Yannone, 1988] describes a hybrid fusion architecture simulation system which combines IRST, ESM, and radar sensor data, resulting in a number of lessons learned in the areas of track initialization/deletion, association, correlation, and track update fusion functions. Measurements as well as track files produced by the sensors are used. For track file initialization, sensor track file outputs are used. When relevant, high priority track measurements are made (e.g., track with shorter range, higher range-rate, emitter identification (ID) and/or mode, shorter time-to-go (TTG)), they are used directly in the fusion process.

The association uses the N out of M method, and then the Kalman filter measurement update equations. Analysis and design parameters are used to quantitatively determine the different fusion algorithm performance. The results of the performance analysis of the different architectures of the simulation system are given below:

Hybrid:
- Good initialization
- Sustained accuracy of target dynamic modelling
- Fault tolerance due to maintaining both the autonomous and centralized fusion architectures.

Autonomous:
- Good initialization
- Degraded accuracy due to temporal extrapolation and mixed target dynamic modelling at the sensor-fusion level.

Centralized:
- Poor initialization
- Sustained accuracy of target dynamic modelling.

The simulation results confirm that the root mean square (RMS) position and velocity errors for centralized architecture is the lowest. The RMS position and velocity errors for hybrid architecture converge to centralized architecture value when the hybrid mode is turned on (i.e. measurement data is used for high priority tracks). The track-to-track fusion (autonomous) performance is much better than for individual sensors alone.

II.2.1.6 System Design Considerations

This paragraph discusses system design considerations for implementing an MSDF function within the AAW frigate of the year 2000 and beyond, described in Task I report.

The selection of the processing methodology and the criteria against which the performance of a fusion system is measured depends upon the user goals and the computational constraints, and should be left up to the particular task that the fusion system is designed to perform (platform type, mission requirements, sensor suite, hardware and software architecture, etc.) [Bowman and Morefield, 1980; Waltz and Llinas, 1990; Thomopoulos, 1990]. The analysis for the selection of the optimal MSDF architecture begins by the following investigations [Buede and Waltz, 1989]:

1. What outputs are desired from the sensors feeding a sophisticated data fusion algorithm?

2. What performance improvements are expected to counterbalance the complex processing requirements of such a fusion algorithm?

Based on the architecture trade-off analysis performed above, a high level analysis of the system design considerations for implementing an MSDF function on the AAW frigate is given below.

II.2.1.6.1 AAW Frigate Overview

The primary task of functional design synthesis is to specify the sensors, processing, communication and display functional requirements that must be met by the physical design of the system [Waltz and Llinas, 1990].

On the AAW frigate the Command and Control (C^2) functions, including the MSDF function, operate within a number of general purpose C^2 processors, communicating with each other and the sensor systems via a high speed data bus. Each processor performs one or more C^2 functions or provides support (display, maintenance, test, etc.) to the CCS operators. The AAW frigate sensors considered within this study are:

1. Radar (medium and long range)
2. IRST
3. ESM
4. IFF.

The following AAW mission types were identified in Task I:

1. Surveillance
2. Protection of reinforcement shipping
3. Protection of high value units (HVU)
4. Area/Barrier operations
5. Point Defence.

Although the purpose of MSDF function is to enhance the system tracking, identification and defence capability against the AAW threats, it will encounter threats of all types:

1. Air
2. Surface
3. Underwater (submarine launched missile)
4. EO/IR
5. Communications
6. Radar
7. Electronic Warfare (EW).

The MSDF function on the AAW frigate must ensure successful accomplishment of its missions and ensure defence against these threats.

II.2.1.6.2 MSDF Performance Considerations

The criteria for evaluating the performance of different multiple target estimation techniques have not been well established in the surveyed literature. Different studies use different considerations, as illustrated in the examples below:

1. In addition to the evaluation of state estimation and prediction errors [Drummond and Blackman, 1989] suggest a variety of measures of performance for an application:

    a. the number of false and missed tracks
    b. probability of misassociation
    c. accuracy of the state covariance matrix

    and performance characteristics for an algorithm so that it can be predicted as:

    a. function of the target destiny
    b. probability of missed and false signals
    c. numbers of new targets, and other error sources.

2. The following criteria have been selected by [Bruder and Farooq, 1990] for comparing the performance of the fusion techniques:

    a. level of fault tolerance
    b. computational burden

  c. amount of inherent parallelism
  d. the ability to compensate for manoeuvring targets
  e. the ability to cope with spatially uncollocated sensors
  f. communication requirement
  g. the ability to handle multiple information rates
  h. the ability to fuse active and passive sensors.

3. [Bowman and Morefield, 1980] list processing options which yield improved accuracy with increasing computational load. The performance requirements and system limitations will be the criteria for those of the following options selected:

  a. single sensor or multiple sensor
  b. single time frame or multiple time frames
  c. single report or multiple reports
  d. positional nearest neighbour or maximum a posteriori algorithm
  e. pretracked and filtered reports or raw reports
  f. kinematics only or probabilistic attributes and kinematics
  g. static prediction models or environmentally adaptive dynamic prediction model
  h. misalignment ignored or higher order misalignment model used.

[Thomopoulos, 1990] includes some examples of how the selection of the fusion architecture is impacted by target tracking and sensor suite considerations:

1. When tracking with multiple sensors, an end result of the fusion must be a target position and velocity estimates. If the presence of the target is ambiguous and the target type itself is not known, detection and identification may precede the estimation (this implies that the MSDF process sequence could be different for different types of tracks).

2. The transformation from the polar to Cartesian coordinate system is non-linear, resulting in a highly undesirable non-linear data fusion model. Hence, in view of these non-linearities, it might be beneficial to group sensors that use the same or linearly related coordinate systems together and fuse their data separately from other groups of sensors that use different coordinate systems that are not linearly related to the former.

The Unisys group working on the FX algorithm simulation system has been using Monte-Carlo simulation to evaluate the Measure of Effectiveness (MOE) of an MSDF algorithm. They have developed a method to benchmark the MSDF algorithm performance and implement it within the FX algorithm simulation system [Wolff, Lutes, Mahler and Fixen, 1991].

II.2.1.6.3 MSDF Architecture within the AAW Frigate

As already discussed above, three MSDF architectures are possible:

1. Distributed, where each sensor creates its own tracks from its sensor data and passes them as tracks or probabilities (hard or soft fusion) to the MSDF function to fuse and establish a master track file
2. Centralized, where raw sensor reports are used in the MSDF processes to establish the state and identification of the objects in the frigate observation space and create a master track file
3. Hybrid, where the sensor systems maintain their track files while the MSDF function uses either track data or raw data in its different processes, depending on the type of hybrid architecture that is selected.

The above mentioned drawbacks of all three architectures are easier to overcome within the distributed computer architecture of the AAW frigate than within a platform with a centralized architecture. The qualitative reasons for this are given below:

1. A distributed MSDF architecture is the logical extension of the distributed computer architecture. To implement fusion with hard-decision sensors, only an MSDF function performing fusion of the track data from the sensor systems is required, operating within the C_2 processor(s) and using the sensor data from the data bus. To implement fusion with soft-decision sensors, additional processing would be added into each sensor system, which would provide multiple hypotheses to the MSDF function via the bus where this information would be fused ensuring high performance. Although this system is straightforward to implement, its performance would not be as good as for the centralized or hybrid architectures.
2. It has been established that the centralized MSDF function has the best performance. However, its requirements for communication, processing and database resources are the highest and maintainability and reliability are the lowest. Within the distributed computer architecture of the AAW frigate the communication, processing and database resource requirements are not as difficult to satisfy. More processors could be added to perform certain processing in parallel, and to ensure adequate database support. This would increase the overhead processing for resource management and communication, but it is expected to be less than if a centralized MSDF function within a centralized computer architecture were implemented. A suitable high speed bus and communication architecture could be selected to support the communication needs. Furthermore very high maintainability and reliability could be ensured within this architecture since redundant copies of the data are maintained and the software can be reconfigured into any processor on

the bus in the case of casualty. This system can also avoid the major drawback of the centralized architecture, that of degrading MSDF performance when one of the sensors is faulted. Within a distributed architecture an on-line maintenance test function that performs automatic corrections or notifies the operators when equipment is faulted can be continuously active.

3. Within this architecture it may be beneficial to select a hybrid architecture too. Having each sensor system do its own tracking in addition to MSDF function, would not have any impact on MSDF processing, could add redundancy, and could be used as a way to gauge MSDF performance when one of the sensors is degraded.

The only anticipated problem for the above systems is the fact that the sensors available be selected for the AAW frigate are not designed to provide measurements (raw data). Without this, even the sensor-level soft fusion MSDF function would not receive the level of detail and speed to ensure the required performance.

Detailed analysis of these considerations among which are [Waltz and Llinas, 1990]: the target capacity; target update rate; communication requirements including message data description, communications performance and message timing; processing requirements including processing architecture, database architecture and contents, and processing algorithms; target state data; target attribute data; data processing for data fusion; and methods of applying parallelism to data fusion including system-level functions and algorithm-level functions, constitute the Task III studies.

II.2.1.7 Analysis for Spatially-Distributed AAW Scenario

The problems and issues in Indirect Fusion (i.e., fusion of data from multiple platforms) are very different from those in Direct Fusion (i.e. fusion of data from sensors within the same platform). In Indirect Fusion, fusing raw data from other platforms is hard to realize due to communication constraints, and because the data from the other platforms have larger errors due to coordinate system conversion (alignment) errors. However the data from other platforms is very useful when data outside of the ownship sensor range is received and for performing bearing only tracking, specifically contact as well as track bearing-to-bearing (2D-2D) and bearing-to-range/bearing (2D-3D) associations.

The Canadian Patrol Frigate (CPF), designed to work in a multi-platform environment in the Naval Force Operations, performs multi-platform tracking. It does not fuse the data from its sensors, but for each track, it displays to the operator the best data available, including the data from remote platforms. Because the data from the remote platforms (after coordinate conversion to ownship coordinate system) may not always be as accurate as the data from ownship, the remote data is kept in separate track stores. However this data can be upgraded to overwrite local data by the operator if the ownship data is degraded or ambiguous. In addition to providing a more complete situation picture, the remote data is used to perform 2D-2D and 2D-3D associations for the ESM and ASW contacts.

In the surveyed literature Indirect Fusion systems are described in [Bowman and Gross, 1985; Feldman, 1988; Drummond and Blackman, 1989]. The approaches taken in these papers are very different:

1. In [Bowman and Gross, 1985] each platform has two data fusion functions. MSI performs Direct Fusion, as discussed above. The track data from MSI is passed to Integrated Surveillance Integration (ISI), where it is fused with the MSI data from other platforms . ISI associates three different types of pairs, 3D-3D, 2D-3D and 2D-2D. A chi-square track association criterion is used. In the 2D-2D case this generates ghost contacts as shown in Figure II.4. To resolve this issue, the ESM sensor emitter parameters are used. (Note that when tree dimensional sensors are used, the probability of ghost tracks is negligible.) In addition to improving the accuracy of these associations, a comparison of time-of-arrival and direction-of-arrival is performed.

2. [Feldman, 1988] describes the ACDS Block 1 real-time automated track management and data fusion system. The data arrives in the form of tracks created by external systems rather than raw sensor data. A common technique for track-to track correlation was developed which is used for remote/local radar tracks, ESM/radar tracks, and ESM line-of-bearing correlation. In this sequential, multiple hypothesis algorithm, candidates for correlation with a new track are selected using an approximative correlation test.

3 [Drummond and Blackman, 1989] discuss a multiple-target-tracking (MTT) system designed for use by a space-based surveillance program, such as Strategic Defence Initiative (SDI). Due to a very large number of targets and very long distances, the approach selected distributes the processing and the track files in a manner similar to that of sensor-level tracking. In this approach, the global track file is partitioned among M tracking platforms. Thus, the track files are partitioned so that each tracking platform only keeps a proportion (1/M) of the total track file. Within each platform central-level tracking is performed. This approach also partitions the processing. Observation-to-track data association is done on the sensor platform where the observations are received while track filter update and gate formation are done at the tracking platforms that contain the tracks. This approach is very flexible because any given platform can function as a sensor platform or a tracking platform, or both. However, this approach requires other platforms to function as backups so that a significant portion of the track file information will not be lost should a tracking platform fail. The major trade-off in this architecture is tracking performance versus the amount of processing resources required.

In the above discussed systems, the [Bowman and Gross, 1985] architecture would be similar to the possible Indirect Fusion architecture implementation on the AAW frigate. In addition to the direct MSDF function, a second data fusion (Remote Fusion) function would be implemented to perform fusion of the track/contact state and attribute data from other platforms with the results of the MSDF function on the frigate. The algorithms discussed in both [Bowman and Gross, 1985] and [Feldman, 1988] could be applied for this system.

The Remote Fusion function architecture analysis must be performed to establish the optimal algorithms and data processing and communication mechanisms best suited to satisfy the needs of the AAW frigate. This is outside the scope of this study. Some limited predictions about the capabilities of this function are made based on the CPF remote data management experience and ISI system implementation discussions in [Bowman and Gross, 1985].

The Remote Fusion function will have multi track fusion algorithms able to fuse all track data from other platforms and limited only by the communication link capabilities between these platforms. It will maintain its track database, which contains the fused data from remote platforms and track solutions from ownship MSDF function. This data will be used by the MSDF association process to resolve ambiguities within associations of ownship data.

The CL-227 Sea Sentinel UAV [Szot and Jones, 1991] can be used with the Remote Fusion function to reduce ambiguities within the MSDF function data. Multiple UAVs can be dispatched to areas not accessible by the AAW frigate sensors or other remote platform sensors due to meterological, geographic or threat conditions to enable the Remote Fusion function to provide the C^2 system with a complete situation assessment picture. UAVs equipped with ESM and IRST sensors will be used to provide contact data to perform 2D-2D and 2D-3D associations.

If it were evaluated that available technology for sensors, navigation equipment and communication links on UAVs could provide compatible data precision with ownship sensors, another alternative would be to integrate the UAVs as another ownship sensor into the MSDF function instead of treating them as remote platforms. However this possibility cannot be confirmed without a more thorough analysis.

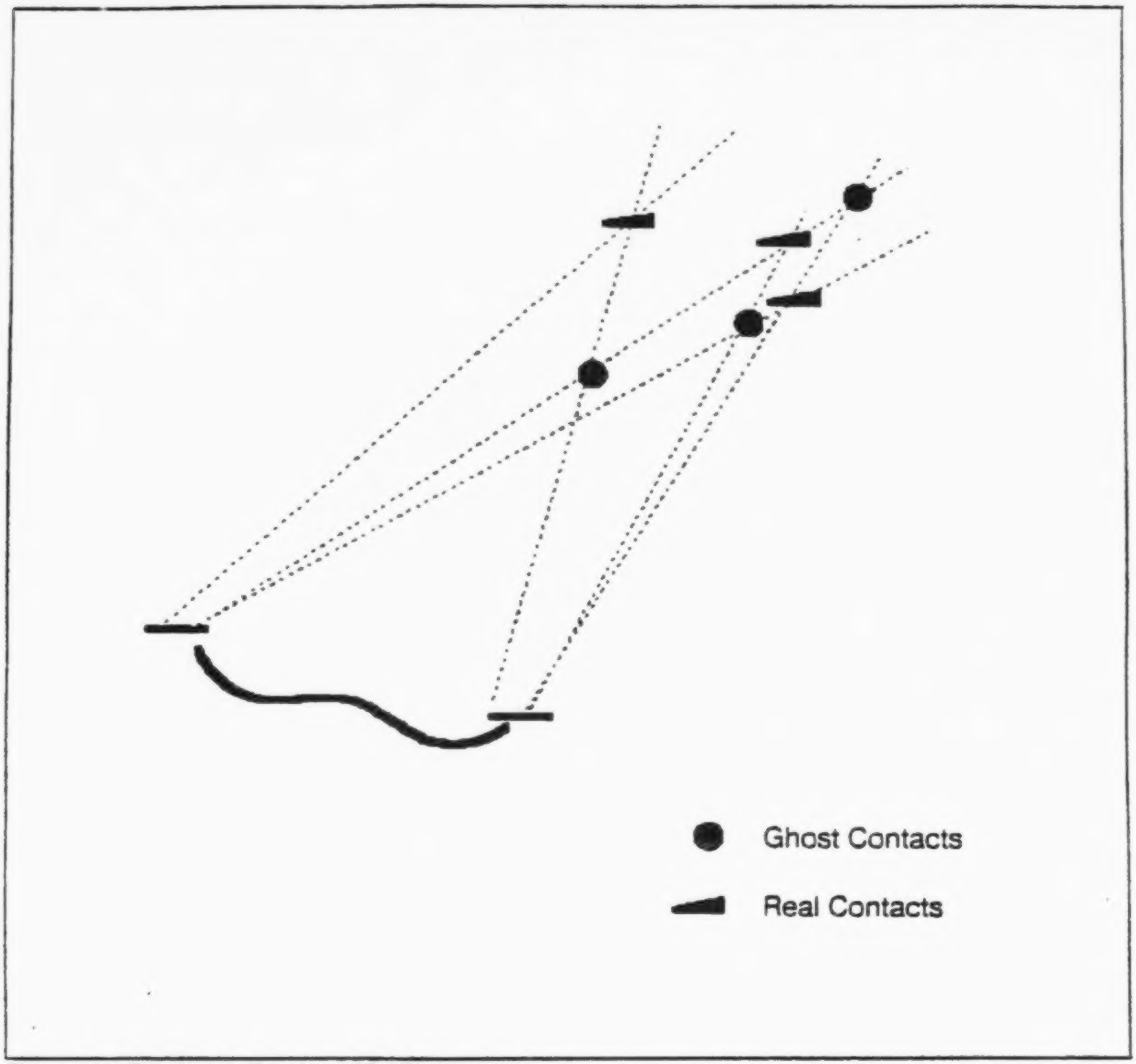
Ghost Contacts
Real Contacts

Figure II.4. Bearing-to-Bearing (2D-2D) Association

II.2.2 Data Association Analysis

II.2.2.1 Introduction

As explained in the architecture analysis section there are two approaches to the MSDF process. One approach assumes that the sensor contacts are sent directly to the MSDF function to be combined into global central-level tracks. In this approach, the data association process is referred to as the contact-to-track association process. The other approach is based on maintaining sensor-level tracks at each sensor site, determining the sensor tracks which potentially represent the same target and then combining these tracks into global tracks of the MSDF function. At this level the association is referred to as the track-to-track association process.

II.2.2.2 Single Sensor Data Association Methods and Techniques

In multisensor and multitarget environments, the association process has to deal with two sources of uncertainties:

1. uncertainty related to sensor measurements
2. uncertainty related to the origin of the measurement.

The first one is a consequence of the technological limitation of any measurement device and the physical properties of the medium between the target and the sensor. The second source comes from external effects which do not originate from the target of interest (wrong target, clutter, decoy, reverberation, etc.) and corrupt the measurement. It is this second source of uncertainties that complicates the association process in a multitarget environment.

Various approaches for handling multiple target association problems are described in the literature. A number of books and review papers specifically address this subject [Blackman, 1986; Bar-Shalom and Fortman, 1988; Blackman and Broida, 1990]. The essence of these analyses is the conversion of the single sensor association methods and techniques to a multiple sensor configuration. The mathematical description of the methods for the single sensor are considered known and just a brief discussion will be included. The main standard techniques and methods of association are:

1. Nearest neighbour
2. Gating
3. Splitting track
4. Probabilistic data association (PDA)
5. Maximum likelihood

6. JPDA
7. Multi-hypothesis method.

The nearest neighbour association method which was developed in the 60s (also called nearest neighbour filter) is applied when more than one contact is obtained during a complete sensor scan. For very low target density, the method selects the contact which has the smallest statistical distance (ratio between squared physical distance and the covariance) to the predicted track measurement. In a multiple target environment, a contact assignment method has to be used. The most popular method is the Munkres algorithm. In environments where false alarm density is moderately high, the tracking system that utilises nearest neighbour method can easily lose the target.

Gating is a technique used to withdraw the unlikely associations between the measured contact and the predicted contact [Sittler, 1964; Singer, 1970]. A gate is usually a hyper-ellipsoid (it has the dimension of the state vector) surrounding the predicted contact. The use of a gate, with certain rules of selection, increases the performance of the filter and avoids spurious associations. The rules are set in relation to the association method used, but all methods require at least the following rule: when only one measurement is within the gate of a single track, the contact is associated with the track.

The splitting track method is based on the fact that if one or more measurements are found in the gate region of an existing track, new tracks are formed by splitting that track [Smith and Buechler, 1975]. For example if two contacts are inside the gate region of a specific track, three tracks will be formed from this track. Each new track represents a hypothesis which respectively assumes that the contact number one belongs to the target of interest and the second contact is noise, the second contact belongs to the target of interest and the first contact is noise, both contacts are noise. The likelihood function (summation of all squared statistical distances of the contacts that form the track) of each track is then evaluated to withdraw the unlikely tracks.

The PDA method evaluates the posterior probability that in the gate region of a particular track, the candidate measurements are associated with the particular track [Bar-Shalom and Tse, 1975]. These posterior probabilities are used to form a weighted sum of innovations (residuals) for processing in a filter. A simple version of PDA algorithm assumes that there is only one target which is observed in the presence of additional measurements that originate from other targets or clutter. The incorrect measurements are assumed to be independent and identically uniformly spatially distributed random variables. The resulting PDA filter yields state estimates and covariances that account for the measurement origin uncertainty.

The maximum likelihood method evaluates the most likely arrangement of contacts in order to establish the tracks corresponding to an unknown number of targets [Stein and Blackman, 1975; Morefield, 1977]. The selection of the possible trajectories is a huge combinatorial problem. To simplify this partitioning problem it can be assumed that each measurement belongs to some track (no false alarm) and each measurement belongs to only one track. The maximization of the appropriate likelihood function of the partition set becomes a typical binary programming problem. Once the most likely set of target trajectories have been chosen from this method, the state vector and covariance matrix of the corresponding tracks are computed from standard filter (Kalman, MLE, etc). This approach is ideally non-sequential and can be appropriate for track initiation. The partitioning process involves the use of parallel programming processing that could increase the processing performance in dense target environments.

The JPDA method is an approach in which a set of established targets is used to form gates in the measurement space and to compute posterior probabilities [Reid, 1979; Fortmann, Bar-Shalom and Scheffe, 1983]. This method is an extension of the PDA method for the multiple target tracking problem. This method associates probabilistically the various measurements to existing tracks and then updates the tracks in a suitable manner. The computation of the probabilities is done jointly for all targets and measurements that form a cluster. Then the weighted innovation is computed for all tracks and in turn is used to update the tracks. This method provides powerful multitarget tracking performance but is not appropriate for track initiation of new targets.

The multi-hypothesis method of association is a method where the decision that a new single contact belongs to an existing single track or is a new track can be deferred [Reid, 1979; Blackman, 1986]. When deferred to the next data scan, the method becomes basically the same as JPDA. This method has the great advantage of successfully processing new contacts that originate initiation of new tracks. Theoretically this method is optimal and ultimately will become the method used by the multi-target tracking systems when the problem of real-time implementation of high computational processing demand is resolved.

II.2.2.3 Sensor Characteristics and Association

Some sensor systems have significantly different detection characteristics and target positional errors. For example, the nature of a passive infra-red sensor is such that its cross-range accuracy is superior to that of an active radar sensor system while its range accuracy is inferior. The technical problem in this case is to take advantage of infra-red sensor cross-range accuracy but radar system range accuracy.

Before association is requested between two different sensor contacts or tracks (depending on the sensor fusion architecture used), a number of association rules must be satisfied. The MSDF function needs these rules to guarantee a maximum utilization of the capabilities of each sensor data. The following paragraphs describe the rules which structure and control the association process between different sensors.

II.2.2.3.1 Gate Test and Dissimilarity Among Measurements

All data association methods rely on gate techniques to eliminate unlikely associations. Each sensor has a certain coverage in common with another sensor. When associating sensor contacts or tracks, it is the data from the common measurement dimension that must be treated in an association gate test. From the sensor suite in this study four gate tests using multi-sensor data can be potentially performed:

1. Range and azimuth gate test:

   The long range radar and the medium range radar both measure range R and azimuth β. Medium range radar also has elevation but the association gate test should use only a two dimensional gate, x and y or R and β, for contact-to-contact and contact-to-track association cases and a four dimensional gate, usually cartesian hyperspace x, y, $\dot{x}$ and $\dot{y}$, for track-to-track association cases.

2. Azimuth only gate test:

   The gate test association between IRST and long range radar, IRST and ESM, ESM and both radars can only be made on the azimuth angle since it is the only common dimension. The gate will be a β interval if association is for contact-to-contact or contact-to-track cases and an ellipse in the space β, $\dot{\beta}$ for track-to-track cases.

3. Elevation and azimuth gate test:

   Since IRST and medium range radar provide information on two angles, the gate test should be performed on elevation θ and azimuth β. The gate will be two dimensional in (θ, β) space for contact-to-contact and contact-to-track association case and four-dimensional in $(\theta, \beta, \dot{\theta}, \dot{\beta})$ space for track-to-track cases.

4. Altitude gate test:

   IFF has a mode where altitude H can be provided. A certain kind of gating test can be built for the IFF and the medium range radar. Using the range R and elevation θ data of the radar, the gate can have the following structure:

$$| H - R*\sin(\theta) | \leq G(H, R, \theta) \quad \text{(II.6)}$$

where the gate G is a function of the variable altitude, range and elevation angle and depends on gating threshold to be discussed later. Association between IFF data and radar data is theoretically feasible. It is very unlikely that such as association would be requested during a typical AAW mission and this possibility is not discussed in published literature reviewed within this study.

II.2.2.3.2 Sensor Resolution and Association Link Structure

Due to the sensor suite used in this study there are four sensor resolution problems which must be taken into account:

1. The high IRST azimuth accuracy makes this sensor capable of resolving multiple targets in a sector where the radar may make a single declaration.
2. Some targets can have multiple emitters. Therefore, ESM may establish multiple contacts from a single target as detected by the radar or IRST sensors.
3. The ESM azimuth is inaccurate compared to that of the radar and IRST; ESM azimuth resolving capability is thus limited.
4. Finally, when multiple targets are closely spaced many different ESM contacts can be resolved, while IRST as well as the radar will not resolve the targets individually.

This last problem is due to the ESM capability to discern the physical properties of different electromagnetic waves. The second and the fourth problems are not easy to surmount since, from the operator point of view, they represent two different but plausible interpretations of a unique tactical picture.

These problems must be taken into account by the association process, especially if the association procedure is automatic. Following the suggestion of [Faragasan and Jakaub, 1989] an automatic track association process must allow multiple association links to reflect different sensor resolution capabilities. Their study describes an algorithm for automatic data association of IRST, ESM and radar tracks within a sensor-level architecture. The arguments developed for track-to-track association can be directly extended to contact-to-contact and contact-to-track association cases within a central-level architecture or hybrid combination. The proposed rules for association link structure are:

1. For each candidate IRST contact or track, no more than one radar contact or track can be associated.

2. For each candidate radar contact or track, any number of IRST contact or tracks can be associated.

These two above rules take into account the azimuth accuracy difference between both sensors. The next four rules are prescribed in order to deal with the second and the fourth sensor resolution problem:

1. For each candidate ESM contact or track, no more than one radar contact or track can be associated.

2. For each candidate radar contact or track, any number of ESM contacts or tracks can be associated.

3. For each candidate ESM contact or track, no more than one IRST contact or track can be associated.

4. For each candidate IRST contact or track, any number of ESM contacts or tracks can be associated.

The second problem will also be treated later during the attribute estimation analysis. The positional information contained in the ESM azimuth is not the only useful data. The tag attribute associated to each ESM contact is an important discriminant for the association process. This tag attribute helps the MSDF function to prune candidate hypotheses and resolve target identity.

The third problem has been exhaustively analyzed by other authors [Trunk and Wilson, 1987; Bennett and Rebovich, 1988]. They suggest automatic association of ESM contacts in a context of multiple hypothesis. The final decision as to which hypothesis corresponds to the radar track (or IRST track) is taken after three to five consecutive positive contact associations from the association process. This decision rule is equivalent to the association of an ESM track with a radar contact or track (similarly for IRST). An ESM track contains azimuth information which is smoothed by a filter and the azimuth variance of the track covariance matrix is smaller than that of the contact.

The conclusion that can be extracted from the literature is that unique association of a single ESM contact with a radar track or contact is not feasible in a multi-target environment. This is due to the large width of the ESM azimuth gate, in which many radar or IRST contacts can be enclosed. The repetitive association process on the next ESM contact reduces the gate size by filtration which eliminates the unassociated radar or IRST contacts.

II.2.2.4 Combined Attribute/Positional Data Association

Until now, emphasis has been put on the positional and kinematic information of the sensor report. In single sensor tracking, identity association and estimation processing is performed independently of positional association processing. In a system where the reports or tracks from multiple sensors are combined, positional and the attribute information should be treated together and included in the same association process [Blackman, 1986, ch. 13]. To perform such association one has to include in the positional association process, an algebra that would permit processing of the attribute information extracted by the sensors. There are various such algebras and the most popular are the Bayesian technique, the Dempster-Shafer evidence theory, and the fuzzy set theory. These techniques are discussed in the attribute estimation analysis chapter. Although positional and attribute associations are not separable in a multi-sensor data association process, the rest of this chapter will concentrate only on the association methods of positional data.

II.2.2.5 Association Within Central-Level Fusion Architecture

The choice of fusion architecture greatly influences the way data association and data fusion processes are performed. For central-level fusion the sensors send their contacts directly to the MSDF function. In such architectures the association and fusion processes deal mainly with contact-to-contact and contact-to-track association and fusion.

II.2.2.5.1 Conversion of Single Sensor Association Techniques to Multiple Sensor Association

In a central-level fusion architecture the data association techniques and methods are almost the same as those for the single sensor with tracking capability [Blackman, 1986]. The difference is mainly in how to fuse optimally passive (no range information) with active sensor data. This question is discussed in section II.2.3.3. The case of passive tracking (more generally the dissimilarity problem) in a central-level architecture has not yet been mastered by the research community. Within the literature surveyed only one paper was found that treats this subject and addresses the central-level track maintenance and initiation [Bernardin and Lin, 1988].

Most of the studies that analyze the data fusion problems within a central-level architecture consider fusion of similar sensors like multisite radar data [Casner and Prengaman, 1977; Cantrell and Grindlay, 1980; Bath, 1982]. The IRST or ESM data are only investigated in the context of sensor-level tracking [Faragasan and Jakaub, 1989; Bennett and Rebovich, 1988; Trunk and Wilson, 1987]. Some association methods and techniques have been outlined in the previous section. The mathematical details of the following data association methods: ellipsoidal gating, nearest neighbour, multiple hypothesis tracking and JPDA are mostly the same as for a single sensor tracking system [Blackman, 1986, p.363]. The only difference pertains to the calculation of the statistical distance where a sensor index, the dimensionality of the measurement matrix and the difference between the covariance measurement matrix have to be taken into account. Also, as explained in more detail in section III.2.2, some modifications have to be made to the Munkres algorithm due to the dimensionality difference between the multiple sensor contacts. The real issue in the implementation of these four methods is the management of the dissimilarity of sensor data in order to perform central track initiation and track maintenance. These operations belong to the fusion and state estimation processes and are discussed elsewhere in Tasks II and III.

II.2.2.5.2 Track Initiation and Maintenance

One of the goals of the MSDF system is to maintain central tracks which provide the necessary information to obtain three-dimensional target position estimates. The medium range radar (MRR) is the only sensor among the ones used in this study that provides three-dimensional position measurements, i.e., azimuth, elevation and range. The IRST sensor does not contain range information. Instead it has the most accurate angle measurement. The MSDF function must exploit the complementarity among the multiple reports in order to perform the track maintenance and initiation.

An example of such exploitation of complementarity among sensors is illustrated in Figure II.5 which depicts a possible way to perform track maintenance (contact-to-track fusion). In this simplistic situation, the gating technique suggests that two synchronized sensor contacts, MRR and IRST, can be associated together (the third gate test described in section II.2.2.3.1) and in addition can both be associated with the extrapolated position of an existing track. The left side of the figure shows a target track position (solid dot), with its 2-σ ellipse (shaded area), extrapolated to the time of arrival of the MRR and IRST. The MRR contact is represented by a little square centred around its 2-σ ellipse and the IRST contact is represented by a line originating from ownship centred around its 2-σ interval.

For simplicity the representation is displayed in the x-y plan. The generalization that includes the elevation measurement is obvious. In the upper right side a new fused contact, indicated by an "X", with a new 2-σ ellipse (cross-shaded area) has been generated from the combination of MRR and IRST reports. The range value of this new fused contact is provided by the radar contact. The azimuth value is obtained from the accurate value of the IRST or from a mixture given by:

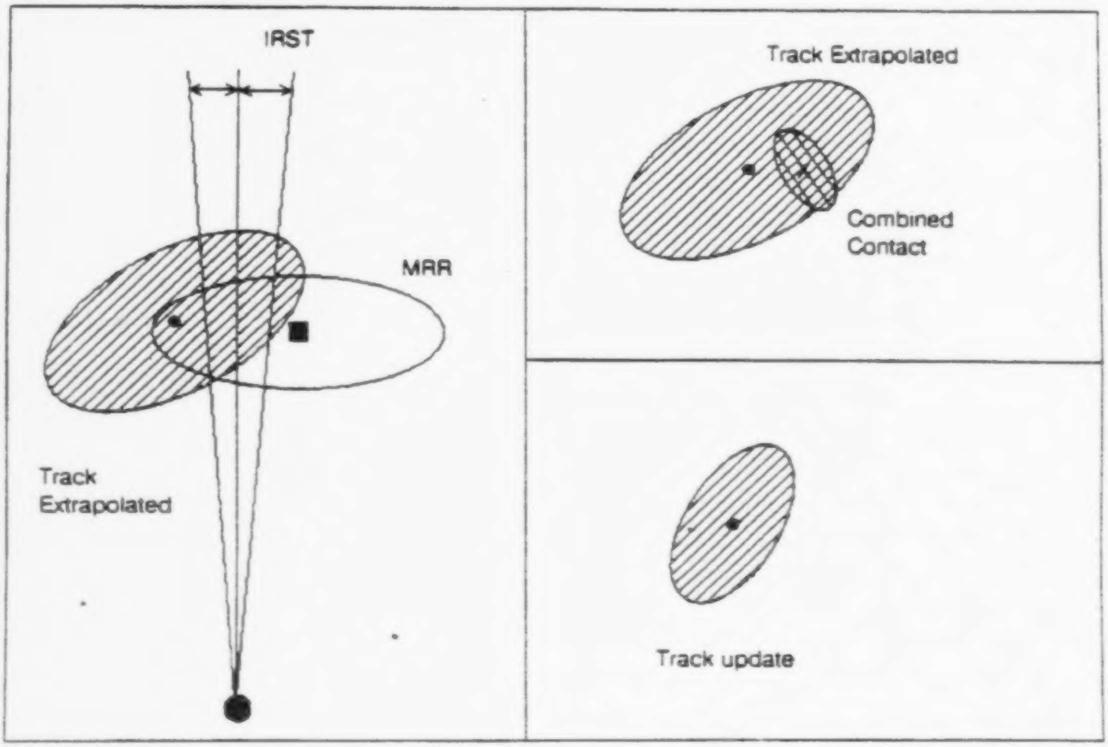
IRST
Track Extrapolated
Combined
Contact
MRR
Track
Extrapolated
Track update

Figure II.5. Contact-to-Track Fusion

$$\beta = \frac{\sigma^2_{\beta_{MRR}} \beta_{MRR} + \sigma^2_{\beta_{IRST}} \beta_{IRST}}{\sigma^2_{\beta_{MRR}} + \sigma^2_{\beta_{IRST}}} \qquad \text{(II.7)}$$

The range variance associated with the new contact will be the same as that of the MRR contact while azimuth variance could be that of the IRST or an optimal one given by:

$$\sigma^2_{\beta} = \frac{\sigma^2_{\beta_{MRR}} \sigma^2_{\beta_{IRST}}}{\sigma^2_{\beta_{MRR}} + \sigma^2_{\beta_{IRST}}} \qquad \text{(II.8)}$$

The lower right side of the figure illustrates the result of the maintenance of the track position estimate. The 2-σ ellipse of the fused contacts is smaller than the 2-σ ellipse of the track that would have been obtained if evaluated using the MRR contact only.

This example is extracted from the work of [Bernardin and Lin, 1988]. The data fusion system presented is designed in such a way that the central-level fusion process computes accurate three-dimensional target tracks filtered by Kalman filter. The central-level fusion process also computes two-dimensional angle tracks to be used by the three-dimensional tracker. These angle-only tracks are obtained from the fusion of azimuth and elevation data from the various sensors and are filtered by a simple α-β filter. The track angle is used to update the main three-dimensional target tracks when radar data is available. Figure II.6 shows a block diagram of such a system. The system has been slightly modified to include the particular sensor suite proper to the AAW frigate study (LRR stands for long range radar.)

After appropriate data alignment methods are performed, all sensor contacts are sent to the association process. The association process performs association logic and false alarm reduction algorithms. The contact data are eventually combined by the data fusion process according to their association declaration tags (one-to-one, multiple or no match). The state estimation process collects the combined new contacts and estimates the state of the target tracks. The states are then directed to the association process for further association with the next scan data.

The original particularity of the Bernardin and Lin system is the false alarm reduction process which transmits the order for track maintenance or track initiation. Four false alarm techniques were considered for the fusion system: Dempster-Shafer, Bayesian, ratio of probability of detection over probability of false alarm and M-or-more sensor. The last technique was retained due a to small computational advantage and mostly because the dissimilarity among sensors ensures uncorrelated noise between them. With this technique a contact is declared as a detection if it is seen by M or more sensors among the N possible.

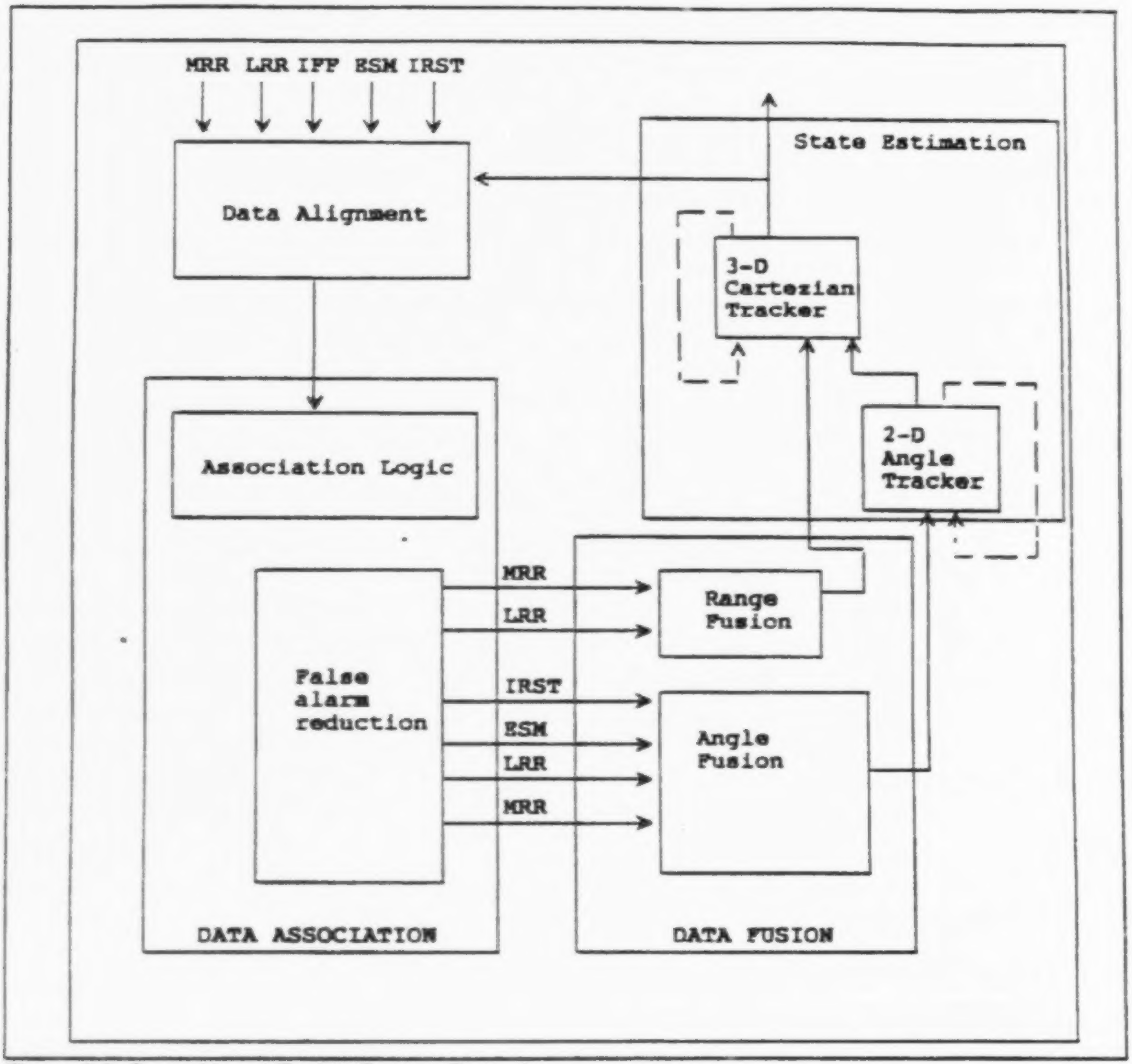
MRR
LRR
IFF
ESM
IRST
Data Alignment
State Estimation
3-D Cartezian Tracker
2-D Angle Tracker
Association Logic
False alarm reduction
MRR
LRR
IRST
ESM
LRR
MRR
Range Fusion
Angle Fusion
DATA ASSOCIATION
DATA FUSION

Figure II.6. Central-Level Fusion System Example

Use or disclosure of data contained on this sheet is subject to the restriction on the title page of this report.

The value of M suggested by Bernardin and Lin is N/2. In the detection system described in their study N=4 so M=2. For example if a target is seen by the MRR it has to be seen by an other sensor to be declared a detection even though the MRR contact could be associated with an existing track. Otherwise it is declared a false alarm and removed from the system. In the Bernardin and Lin system the detection ranges of the sensor suite are approximately equal. In the case of the AAW frigate it must be taken into account that a target inside the range of the LRR is not necessarily inside the range of the MRR, and consequently the target can stay undetected by the MRR or any other sensor. Therefore, the rule M=N/2 may not be appropriate for this case.

The initiation of a new track is performed if a single contact has successfully survived the false alarm reduction requirement and is declared "no-match" by the association logic process. If it is declared "one-to-one" or "multiple" to some existing tracks it is used for track maintenance.

As shown in the state estimation box of Figure II.6, the use of a separate angle-only tracker for the azimuth and elevation data is not an optimal way to perform the track initiation operation. Since the goal is to get a three-dimensional state vector with a minimal covariance matrix, it is preferable that the initiation process be started with the angle-only contact in spite of the absence of range information. Most of the time, the state estimation process is done by adaptive linear Kalman filter in cartesian coordinates, and without range information it is impossible to use the angle information optimally. For track maintenance the situation is less problematic since the state has enough information to estimate a range. But again, the filter update with angle-only data will not be optimal. A way to solve the problem resides in the use of extended Kalman filter of modified spherical coordinate Kalman filter. These filtering techniques are explained in sections II.2.3 and II.2.8.

II.2.2.6 Association Within Sensor-Level Fusion Architecture

In sensor-level architecture the fusion process combines tracks from the various sensor tracking systems. In contrast to the previous architecture, the sensor-level architecture is well documented [Singer and Kanyuck, 1971; Bar-Shalom, 1981; Chong, Mori and Chang, 1986]. It has been exhaustively studied and applied in many prototype systems [Hall and Linn, 1991]. The following sections outline the major implications of track-to-track association in such an architecture. The fusion philosophy under consideration is the one where the MSDF global tracks are established periodically from sensor selection and/or a combination of sensor tracks instead of the approach where the MSDF global tracks are continuously updated from fusion with sensor track data each time a sensor system makes it available.

II.2.2.6.1 Track-to-Track Gating and Correlation

The association process has to evaluate if two sensor tracks represent the same target or not. This problem has been investigated by [Bar-Shalom, 1981]. Let us consider two six dimensional cartesian state vectors $\vec{X}_a(k)$ and $\vec{X}_b(k)$ corresponding to sensors a and b respectively. Here both state vectors have been aligned to the same time by extrapolating the tracks to the current MSDF scan time. The ellipsoidal gate R, which is used to estimate the degree of correlation between the two tracks, is obtained from:

$$R^2 = (\vec{X}_a - \vec{X}_b)^T U^{-1} (\vec{X}_a - \vec{X}_b) \le G \qquad \text{(II.9)}$$

Where U is a covariance matrix associated with the difference between both state vectors. G is the gate value. An approximative expression for the covariance will neglect the common process noise. In this case the covariance is simply the sum of both sensor track covariance matrices:

$$U = P_a(k) + P_b(k) \qquad \text{(II.10)}$$

R^2 is a chi-square random variable with six degrees of freedom. A typical value of G, for six degrees of freedom, is 12.4 or 16.8 for a 95% or 99% level of confidence respectively.

After the gating technique is implemented the association technique can be any of the ones mentioned in section II.2.2.2. The nearest neighbour method is a natural choice since each sensor tracking system has its own false alarm reduction function which substantially reduces the probability of misassociation.

II.2.2.6.2 Correlation Due to Common Process Noise and Repeated Fusion

As previously mentioned the expression (II.10) is an approximation that neglects the process noise included in each sensor tracking algorithm. This process noise is part of the target dynamic equation and has a covariance matrix Q. It has been shown that the exact treatment [Bar-Shalom; 1981] includes the process covariance Q matrix and each sensor Kalman gain matrix if Kalman filtering is used, which is usually the case. This slightly complicates the equation (II.10) which becomes:

$$U = P_a(k) + P_b(k) - CP_{ab}(k) - CP_{ab}(k)^T \tag{II.11}$$

The cross covariance matrix CP_{ab} is given by

$$CP_{ab}(k) = [I - K_a(k)H_a]B(k-1)[I - K_b(k)H_b] \tag{II.12}$$

where

$$B(k-1) = \Phi_a CP_{ab}(k-1)\Phi_b^T + Q(k-1) \tag{II.13}$$

where H, K, and Φ are respectively the measurement matrix, the Kalman gain matrix and the transition matrix for each sensor. The initialization of CP_{ab} is

$$CP_{ab}(k=0) = 0 \tag{II.14}$$

This exact calculation is, however, only valid for two sensor fusion. The case where three or more sensor tracks correlate has not been assessed. For the system under investigation on the AAW frigate this problem will probably not be encountered [Yannone, 1988; Blackman and Broida, 1990, p. 456]. The sensor suite on the frigate, which is composed of five dissimilar sensors, makes direct fusion of three sensor tracks unlikely. This last statement will be investigated later in the data fusion analysis chapter.

The alternative to the periodic re-establishment of MSDF global tracks is the continuous update of the MSDF tracks using sensor track data when each sensor track is updated from new measurements. The fusion between filtered data and the MSDF global track cannot be performed like contact data and MSDF global track. Filtered data are time correlated and repeated fusion of these data will bias (underestimate the covariance) the global track if the fusion is performed without appropriate restrictions. These restrictions are not analyzed in the literature. It is suggested that this approach should be avoided [Blackman, 1986, p. 387].

II.2.2.6.3 Implementation of Multi-Hypothesis Tracking Techniques

The multi-hypothesis tracking method was first developed for contact-to-contact and contact-to-track association and fusion [Reid, 1979; Mori, Chang, Tse and Wishner, 1986]. For track-to-track association and fusion the method must be modified. The modification to the statistical formalism has been introduced in [Chong, Mori and Chang, 1985 and 1986] for a general distributed sensor network where the global MSDF tracking is distributed over the nodes of local processors and sensors. Another global tracking mechanism called hierarchical [Chong and Mori, 1984a and 1984b] has also been developed. The distributed sensor network approach is more appropriate to the study of the AAW frigate since the sensors can be grouped into two local nodes: passive sensors (ESM and IRST) and radar (MRR, LRR and IFF) sensors to extract a local node track. These local node tracks are eventually associated and fused to form the global MSDF tracks. The subject is too broad and complex to be discussed here. A separate study to address this topic is proposed in section VI 2.2.2. All the details concerning the algorithm of multi-hypothesis tracking for sensor-level are presented in [Bar-Shalom, 1990, ch. 8.4].

II.2.3 Data Fusion Analysis

II.2.3.1 Introduction

The data fusion process is responsible for the combination of the associated data coming from the association process. The specific functional and performance requirements of this process depend upon the fusion architecture selected for the MSDF. The nature of the combination must also take into account the dissimilarity between the sensors in order to exploit the complementarity of the various data as much as possible. This chapter presents fusion techniques and methods that overcome the dissimilarity problem.

II.2.3.2 Fusion within Central-Level Sensor Architecture

II.2.3.2.1 Appropriate Fusion Techniques

Theoretically there are three methods of fusion which can be applied to combine sensor contacts in a central-level architecture MSDF function [Willner, Chan and Dunn, 1976; Bruder and Farooq, 1990]. These methods are called sequential processing, parallel processing and data compression. Depending upon whether the sensor data are synchronised or not, these methods are applied differently. The following paragraphs describe each methodology when the sensor data are synchronized.

The sequential processing method combines the various sensor contacts sequentially with abstraction of time, i.e., in setting Δt to zero in state matrix Φ, which becomes the identity matrix, and in introducing an additional index (sensor index) to the filter equations.

The parallel processing directly updates the MSDF global tracks in one step by calculating a residual for each sensor contact. Each residual is multiplied with an appropriate gain and the products are summed together. The result is then used to update the track state vector.

In data compression the contacts are grouped according to their similarities. The goal is to produce a fused contact from the best information contained in the contact of each different sensor. This "artificial contact" is used to initialize and maintain the MSDF track. An example of data compression is represented by a functional process data flow diagram in Figure II.7. The design is inspired from the work of [Bernardin and Lin, 1988].

The parallel and sequential processing techniques can be applied more easily if the sensors are similar, but with a suite of very dissimilar sensors the mathematical formalism needs deep modification. The surveyed literature concentrates on the application of these methods only for similar multisensor systems. Data compression appears to be the only technique that can be directly applied to the sensor suite of this study.

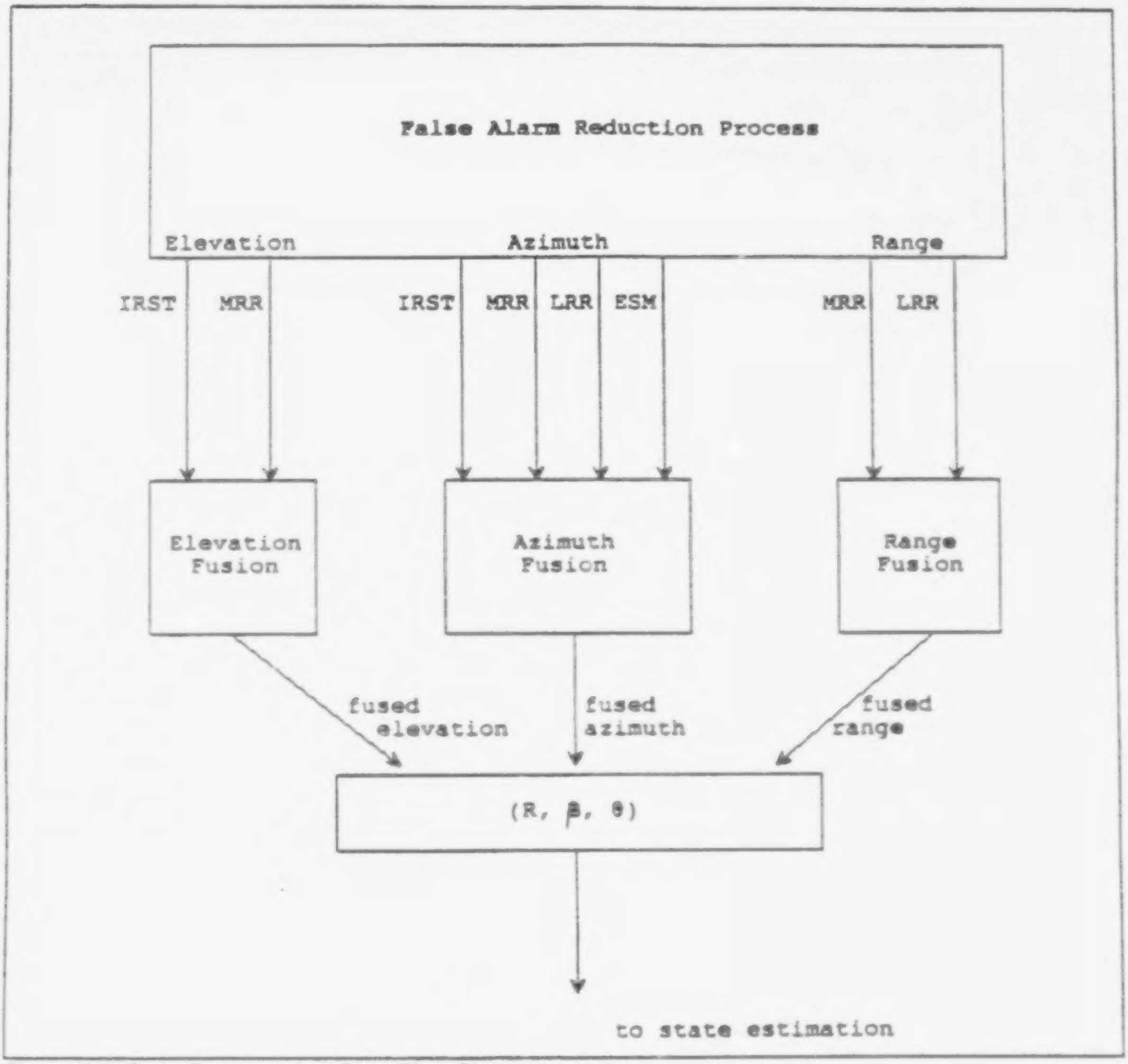
False Alarm Reduction Process
Elevation
Azimuth
Range
IRST
MRR
IRST
MRR
LRR
ESM
MRR
LRR
Elevation Fusion
Azimuth Fusion
Range Fusion
fused elevation
fused azimuth
fused range
(R, β, θ)
to state estimation

Figure II.7. Data Compression Data Flow Diagram

II.2.3.2.2 Exploitation of Complementarity Among Various Measurement Vectors

The data compression method of fusion has to exploit the complementarity among the sensor contacts optimally. Bernardin and Lin suggest fusing the sensor angle information and the sensor range information separately and using the resulting range and angle information in the central track. Other references suggest using only the best information from each sensor [Blackman and Broida, 1990]. As an example, in the context of the AAW frigate, the compressed contact would have range from the MRR, angles from the IRST and attribute information from the ESM. These two methods contain limitations and assumptions. The limitation in the Bernardin and Lin system is that they suppose synchronization of the incoming contacts which is a restriction difficult to ensure technically.

The particularity of both methods is that fusion is performed only on similar information which is common to each sensor. The MSDF global tracks are built from the artificial contacts that result from a separate fusion of range, elevation and azimuth information. Figure II-7 sketches an ideal data compression system which could, in principle, be applied to the AAW frigate. The contacts that successfully meet the false alarm reduction algorithm of the data association process are divided according to the dimension of their measurement vectors. The sensor range information is fused to extract an optimal range value. Azimuth and elevation information have a similar treatment. The output range, elevation and azimuth are grouped to form a measurement vector which will update an MSDF global track.

II.2.3.3 Fusion Within Sensor-Level Sensor Architecture

II.2.3.3.1 Track Fusion when Confronted With Track Error Correlation

When the target model of the filtering function includes process noise, the combination of two tracks associated to the same target should include the cross covariance matrix between the two tracks. The cross covariance matrix CP_{ab} is given by expression (II.12) of the data association analysis chapter. For two correlated tracks that have been previously time aligned, the fused track state is expressed as

$$\vec{X}_{fu} = \frac{(P_b - CP_{ab}^T)\vec{X}_a + (P_a - CP_{ab})\vec{X}_b}{P_a + P_b - CP_{ab} - CP_{ab}^T} \qquad \text{(II.15)}$$

and the fused covariance matrix related to this fused track is obtained from

$$P_{fu} = \frac{P_a P_b - CP_{ab} CP_{ab}^T}{P_a + P_b - CP_{ab} - CP_{ab}^T} \tag{II.16}$$

Equations (II.15) and (II.16) are extracted from [Bar-Shalom and Fortmann, 1988 ch. 10.3] and [Blackman, 1986 appendix 13A]. Their results are slightly modified here in order to preserve the symmetry against inversion of the indices a and b.

It is obvious that the fusion between tracks a and b should be equal to the fusion between b and a. This invariance against inversion between a and b is warranted from the definition of the cross covariance matrix [Bar-Shalom, 1981]

$$CP_{ab} = E\{(\vec{X}_a - \langle\vec{X}_a\rangle)\,(\vec{X}_b - \langle\vec{X}_b\rangle)^T\} = CP_{ba}^T \tag{II.17}$$

where the notation E{} stands for the expected value of a random variable and <> the averaged value, obtained from:

$$\langle\vec{\boldsymbol{X}}_a\rangle = E\{\,\vec{\boldsymbol{X}}_a\,\} \tag{II.18}$$

II.2.3.3.2 Fusion of Many Sensor Tracks

The previous section deals with the fusion of two tracks without explicitly describing how to initialize and maintain the global MSDF tracks, when a third (and generally many) sensor track is fused. This problem has not yet been addressed rigorously but the functional principle is known [Blackman, 1986, ch. 13.3.2] and a generalization to many sensors appears to be feasible according to [Broida et al, 1989]. A functional process for the periodic track fusion of many sensors is shown in Figure II.8. The flow of the information between the sensors and the MSDF database in which the global fused tracks are stored is indicated. The first sensor is usually the best one because if a new target is detected by many sensors, including the best one, then a new MSDF track will be initialized using this sensor track value. If other sensors have detected this new target, their track data will be used to update the new global MSDF previously initialized track.

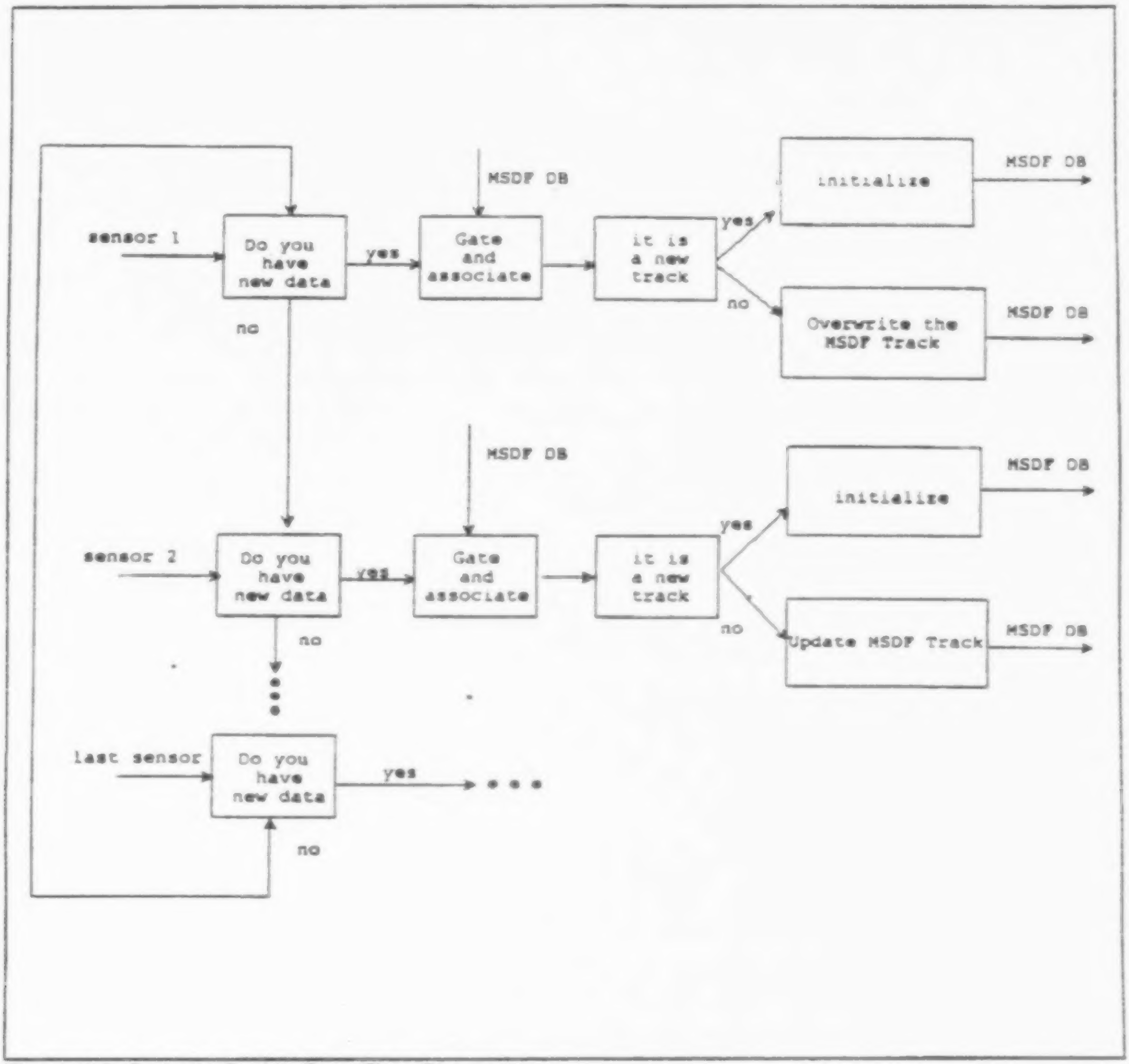
MSDF DB
sensor 1
Do you have new data
yes
Gate and associate
it is a new track
yes
initialize
MSDF DB
no
Overwrite the MSDF Track
MSDF DB
no
MSDF DB
sensor 2
Do you have new data
yes
Gate and associate
it is a new track
yes
initialize
MSDF DB
no
Update MSDF Track
MSDF DB
no
last sensor
Do you have new data
yes
no

Figure II.8. Periodic Fusion Data Flow Diagram

Recently [Blackman and Broida, 1990] have suggested an algorithm which is extended here, and which approximately takes into account the inclusion of a third (or more) sensor track. It was noted that the effect of the cross covariance matrix is to increase the resulting fused covariance matrix. Thus the above algorithm fuses the tracks without considering the cross covariance but readjusts the fused covariance if the decrease in the variance is too high. The steps of the algorithm are as follows:

1. The first sensor is interrogated by the MSDF function. If the sensor has new data the association process is requested to compare the new sensor data with the already existing MSDF track. If it is a new track, the initialization of the new MSDF track is given by the sensor itself. If the sensor track exists in the MSDF, the MSDF function overwrites its information with the sensor data. This process is not an update or an initialization but something in between. The MSDF function keeps its exclusive information (if some exist [Blackman, 1986]) and re-establishes only the data of the type (positional, velocity, course, etc.) provided by the sensor. Therefore, the new MSDF track state vector and covariance is given by:

$$\vec{x}_{new} = \vec{x}_{S_1} \quad \text{and} \quad P_{new} = P_{S_1} \tag{II.19}$$

2. Then a second sensor is interrogated. If the sensor track S_2 is reported to correlate with the already established fused track, the fusion process must combine this sensor track. First, the following new fused covariance matrix is tentatively computed from:

$$P_{new} = \frac{\rho \; P_{old} P_{S_1}}{P_{old} + P_{S_1}} \tag{II.20}$$

   where P_{old} is the fused covariance before the track S_2 is received and ρ a phenomenological parameter to be determined. Let α be the smallest amongst the ratios between each diagonal element of P_{new} and its corresponding diagonal element of the previous P_{old}.

$$\alpha = Smallest\left(\frac{Dia(P_{new})}{Dia(P_{old})}\right) \tag{II.21}$$

The value of ρ is obtained from the following test:

$$\rho = \begin{Bmatrix} 1, & if & \alpha \geq 0.7 \\ \frac{0.7}{\alpha}, & if & \alpha < 0.7 \end{Bmatrix} \tag{II.22}$$

This test has the role of simulating the effect of the true cross covariance matrix. After this test is performed and the P_{new} is assessed a new fused state vector can be evaluated.

$$\vec{\boldsymbol{x}}_{new} = \vec{\boldsymbol{x}}_{old} + \left[\frac{P_{new}}{P_{new} + P_{S_2}}\right](\vec{\boldsymbol{x}}_{S_2} + \vec{\boldsymbol{x}}_{old}) \tag{II.23}$$

where the indices old and new refer to the fused state vector before and after the actual sensor track S_2 is fused.

3. When a track S_3 of a third sensor also correlates, the fusion equations (II.20) to (II.23) are reprocessed with S_3 and the indices old and new indicate the fused track before and after the sensor track S_3 is fused.

4. When all sensors have been interrogated the fusion process is finished. The interrogator returns to the first sensor and starts the fusion process again.

II.2.3.3.3 Method to Maintain the Central-Level Track Using the Sensor-Level Track

Here, some questions raised about the methods used to maintain the global MSDF tracks are answered. The questions are formulated in the context of this study and the answers are inspired from [Blackman and Broida, 1990, ch. VI].

1. Should the update of the global MSDF tracks be performed with sensor-level track or with selected observations from the sensors?

This question is equivalent to asking if MSDF should perform sensor-level architecture fusion or central-level architecture fusion. The architecture analysis addresses this issue.

2. Should an MSDF global track consist of fusion of sensor tracks or the use of the "best" sensor track?

   In the context where many spatially distributed platforms using many sensors are integrated into a fusion system it could be advantageous to retain only the high quality tracks from the best sensors as the global fused track. The AAW frigate situation is different since only five sensors are used and they are very dissimilar. The MRR sensor is the only sensor that provides a complete six-dimensional target state. This condition is necessary to the MSDF global track but MRR does not cover targets at long ranges. IRST provides better angle accuracy than MRR, and ESM provides some attribute information that is not always available with the MRR. The fusion of all available sensors, performed in such a way as to exploit the complementarity among the various state vectors, is thus more appropriate than using best sensor tracks approach.

3. Should the MSDF global tracks be periodically re-established by fusion of sensor tracks or be continuously updated using sensor track estimates?

   The first method used in section II.2.3.3.2 is a pure track-to-track fusion method. The second approach does not perform track-to-track fusion, but instead a pseudo-estimate-to-track fusion. The estimates are obtained from the sensor tracks and are treated like "contacts". In a pure contact-to-track fusion process, the contacts are combined by using filtering techniques. Estimate-to-track fusion should be applied with caution due to the time correlation (violation of time independency principle) between sensor estimates and global tracks. References [Lacoss, 1987; Tenney and Delaney, 1984] address this time correlation problem. The second approach appears to be computationally simpler and faster than pure track-to-track fusion but the time correlation problem is still not satisfactorily solved.

II.2.3.3.4 Exploitation of the Complementarity Among Various State Vectors

The exploitation of the complementarity among the different sensor state vectors cannot be reflected in the fused tracks in the same way it is performed in a central-level architecture. The appropriate combination of a passive sensor track with an active sensor track or an X-Y track with an X-Y-Z track are examples of exploitation of complementarity. In a central-level architecture, the data compression technique consists of building an artificial contact from a mixture of elements of various sensor contacts. In sensor level fusion, the technique described in section II.2.3.3.3 applies only to the fusion of tracks of the same coordinate system and dimensions. To apply the periodic establishment fusion technique to the sensor suite of the AAW frigate, equations (II.20) and (II.23) must be modified to exploit the complementarity among the dissimilar sensor tracks. The exploitation of the complementarity is strongly dependent on the sensor suite utilised by the platform. The literature surveyed does not specifically address a sensor suite similar to this study. The following paragraphs present the PARAMAX concepts about ways to modify the equations (II.20) and (II.23) and the transformation of the coordinate systems in order to exploit the complementarity among various state vectors.

The ESM and IRST tracking algorithms use polar coordinates to represent their state vector and covariance matrix. The missing range information does not permit a transformation in cartesian coordinates. The range information of the active sensor MRR and LRR allows the utilization of cartesian coordinates. Filtering of the radar contacts in polar (r, β) and spherical (r, β, θ) coordinate system is relatively new in AAW but well known in ASW [Stallard, 1987; Hassab, 1989]. A necessary requirement for the fusion between the sensors dictates that the radar state vectors and covariance matrices be translated into the spherical coordinate system. When all sensor tracks are given in the same coordinate system, fusion is theoretically possible. The final fused global tracks which are in the spherical coordinate system can thus be retransformed into the cartesian coordinate system for future processing.

The ESM azimuth tracks have a state vector and covariance matrix of the following structure:

$$\vec{x} = \begin{bmatrix} \beta \\ \dot{\beta} \end{bmatrix} \qquad P = \begin{bmatrix} \sigma_{\beta}^{2} & \sigma_{\beta\dot{\beta}} \\ \sigma_{\beta\dot{\beta}} & \sigma_{\dot{\beta}}^{2} \end{bmatrix} \tag{II.24}$$

The IRST elevation and azimuth track structure is:

$$\vec{x} = \begin{bmatrix} \beta \\ \theta \\ \dot{\beta} \\ \dot{\theta} \end{bmatrix} \qquad P = \begin{bmatrix} \sigma_{\beta}^{2} & \sigma_{\beta\theta} & \sigma_{\beta\dot{\beta}} & \sigma_{\beta\dot{\theta}} \\ \sigma_{\beta\theta} & \sigma_{\theta}^{2} & \sigma_{\theta\dot{\beta}} & \sigma_{\theta\dot{\theta}} \\ \sigma_{\beta\dot{\beta}} & \sigma_{\theta\dot{\beta}} & \sigma_{\dot{\beta}}^{2} & \sigma_{\dot{\beta}\dot{\theta}} \\ \sigma_{\beta\dot{\theta}} & \sigma_{\theta\dot{\theta}} & \sigma_{\dot{\beta}\dot{\theta}} & \sigma_{\dot{\theta}}^{2} \end{bmatrix} \tag{II.25}$$

The convenience of the spherical coordinate system is that the azimuth information of the ESM can be coupled or combined with the azimuth information of the IRST in a trivial way (linear equation) by the use of an appropriate "measurement matrix". As an example, a naive fusion between the ESM and the IRST covariance would be

$$P_{fu} = \left[P_{IRST}^{-1} + \left(H P_{ESM}^{-1} H^{T}\right)\right]^{-1} \tag{II.26}$$

where H is a 4X2 matrix which projects the azimuth space of the ESM data into the azimuth-elevation space of the IRST data. From equations (II.24) and (II.25), the appropriate matrix H should be written as:

$$H = \begin{pmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix} \tag{II.27}$$

The situation of the LRR and MRR are different because their tracks are usually computed in the cartesian coordinate system. The state vectors are of this form:

$$\vec{X}_{LRR} = \begin{pmatrix} x \\ y \\ \dot{x} \\ \dot{y} \end{pmatrix} \qquad \vec{X}_{MRR} = \begin{pmatrix} x \\ y \\ z \\ \dot{x} \\ \dot{y} \\ \dot{z} \end{pmatrix} \tag{II.28}$$

Transformation into the spherical coordinate system is straightforward and obtained from:

$$R = (x^2 + y^2 + z^2) \qquad \textbf{(II.29)}$$

$$\beta = \arctan\left(\frac{x}{y}\right) \qquad \textbf{(II.30)}$$

$$\theta = \arctan\left[\frac{z}{\sqrt{x^2 + y^2}}\right] \qquad \textbf{(II.31)}$$

$$\dot{R} = \frac{x\dot{x} + y\dot{y} + z\dot{z}}{(x^2 + y^2 + z^2)^{1/2}} \qquad \textbf{(II.32)}$$

$$\dot{\beta} = \frac{y\dot{x} - x\dot{y}}{(x^2 + y^2)^{1/2}} \qquad \textbf{(II.33)}$$

$$\dot{\theta} = \frac{x^2\dot{z} + y^2\dot{z} - xz\dot{y} - yz\dot{x}}{(x^2 + y^2 + z^2)(x^2 + y^2)^{1/2}} \qquad \textbf{(II.34)}$$

These equations are strictly valid for MRR. For LRR the equations (II.31) and (II.34) are not computed and the equations (II.30) and (II.32) are computed with $z = 0$.

The transformation of the 10 and the 21 cartesian elements of the MRR and LRR covariance matrix in spherical coordinates is obtained from the following summation:

$$\sigma_{fg} = \sum_{l=1}^{6\,or\,4} \sum_{m=1}^{6\,or\,4} \left(\frac{\partial f}{\partial x_l}\right)\left(\frac{\partial g}{\partial x_m}\right)\sigma_{x_l x_m} \qquad \text{(II.35)}$$

In this equation f and g stand for any polar variables represented by the equations (II.29) to (II.34), x_l or x_m stand for any cartesian variables. In (II.35) it is implicitly assumed that

$$\sigma_{x_m x_m} = \sigma_{x_m}^2 \qquad \text{(II.36)}$$

When all the coordinate transformations are performed, the radar tracks can theoretically be combined with the ESM and IRST tracks. The combination will be performed similarly using the method explained in section II.2.3.3.3 for the condition that appropriate measurement matrices are included in equation (II.20) and (II.23). The determination of these matrices could be the subject of another research project. The literature surveyed does not discuss this. From discussions about equation (II.26) it can be concluded that, for example, the fusion between the MRR track and IRST will require a measurement matrix of dimension 6X4. New research should be aimed at finding what these matrices are and where they evolve in equations (II.20) and (II.23).

Finally the facility to fuse passive and active sensor data will be discussed when the performance of each fusion technique is evaluated in sections III.2.2 and III.2.3. The technique which is most appropriate when active sensors are employed sparsely to increase the passive track quality is addressed in section III.2.4.

II.2.3.3.5 Impact of the Target Dynamics Model on the Track Fusion Process

Unlinearities like manoeuvres and coordinate transformation equations are usually taken into account by the process noise term in the state dynamics equation. A bad modelling or the exclusion of the noise process term will bias the fused state estimate and bear results of lesser quality than the stand alone sensor track. The effect of the exclusion of the common noise process on the fused track has been investigated by [Blackman and Broida, 1990] and [Yannone, 1988]. Yannone concludes that the exclusion has a negligible effect on his results. On the other hand, Figures 3 and 4 of the Blackman and Broida article clearly show the necessity to include the same target dynamics model on the fused track equations.

II.2.4 Data Alignment (Registration) Analysis

II.2.4.1 Introduction

The combat system on a frigate comprises sensor, weapon and navigation subsystems which operate together with the CCS to function in support of the mission requirements. Each subsystem provides positional data with respect to a coordinate reference frame. If all data used by the CCS is not reported with respect to the same reference frame, considerable difficulty as well as significant errors will occur. The usual design strategy is to select a standard reference frame as the basic reference frame within a platform and to convert any system measurements made in a frame other than in the standard frame, into the standard frame.

Two reference frames may be displaced from each other by a distance measured between their reference points and may be rotated with respect to each other so that their reference directions or reference planes are not parallel. The corrections made necessary by the linear displacement between the reference frames are called "parallax" corrections and those made necessary because the frames are not parallel are called "rotation" corrections [NAVORD OP 762, 1960]. It is extremely important to first perform a thorough alignment of subsystem installations to minimize these rotational and translational displacements. Remaining displacements are due to the fact that parallax correction is a function of target distance, the spherical shape (approximate) of the earth mounting and calibration error (bias error), and random error (platform flexing and vibrations). This displacement is corrected by algorithms within the CCS. Displacement problems of this type are referred to as spatial alignment problems within the same platform.

Another type of positional displacement problem that exists within the data received by the CCS is alignment errors between the reference systems of different platforms involved in multi-platform operations. These problems are corrected by CCS by algorithms called gridlock corrections or registration. They are referred to as multi-platform spatial alignment problems.

The fact that data from different subsystems on a frigate does not usually arrive at the CCS at the same time can also cause considerable difficulties and errors. There are many different temporal displacement problems such as different data rates, out of sequence measurements, synchronization, interpolation, extrapolation, buffering, time latency, and bias errors (sensor clock time). Temporal displacement problems must also be corrected, or if they cannot be explicitly evaluated, their impact must be accounted for by the C^2 functions. The corrections which must be applied to account for temporal displacement problems are made by algorithms within the CCS. These problems are referred to as time alignment problems.

The algorithms to correct for the above mentioned three displacement problems are referred to as data alignment or registration techniques.

II.2.4.2 Data Alignment Techniques

In various circumstances, due to either geographical disparity or misalignment, different sensors may not gather data from precisely the same geographical region, or may not observe the same phenomenon or process simultaneously. When the mismatch cannot be resolved from the data collected from different sensors, the mismatch must be modeled mathematically. When a mathematical model for the sensor mismatch is not available, data fusion should take place at the signal level by taking into consideration the constraints imposed by the problem and sensor physics [Thomopoulos, 1990].

Thirteen studies were found within the surveyed literature that discuss data alignment techniques. Most of the literature surveyed does not address the alignment problem at all. A few mention that alignment is part of a data fusion system, but do not discuss it [Reid, 1979; Wright, 1980; Reiner, 1985; Fernandez, 1985; Comparato, 1988; Blackman and Broida, 1990]. Martin P. Dana in [Bar-Shalom, 1989, ch. 5] states that the registration of multiple sensor systems, in general, has been inadequate. The problem does not seem to be understood or even recognized beyond a small circle of systems engineers at a few government laboratories and aerospace companies. Registration, it seems, has been an afterthought in most multiple sensor systems.

The most well understood and analyzed data alignment techniques are the multi-platform spatial alignment problems and techniques [Fisher, Muehe and Cameron, 1980; Bath, 1982; Feldman, 1988; Bar-Shalom, 1989, ch. 5].

There are five studies where the spatial alignment problems within the same platform are addressed. However, only three [Bowman, 1979; Beaulieu, 1985; Fritz, 1989] studies apply to the analysis of the alignment problems within a naval platform.

The time alignment problems are not sufficiently discussed within the surveyed literature. [Fritz, 1989] addresses extrapolation, interpolation and time latency issues and [Thomopoulos and Zhang, 1988A&B; Thomopoulos, 1990] discuss different data rates, out of sequence measurements and synchronization. Other problems are mentioned in some of the thirteen papers found, but are neither studied nor evaluated.

[Fritz, 1989] states that to implement a multi-sensor tracking algorithm, the most important platform characteristics to be known before design is the nature of the data that will be produced by sensors.

Specifically, the measurements, measurement rates, and errors in measurement should be known before design. For most sensors, the measurement values and rates are well known, but the errors associated with measurements are often not known or not reported by the sensors. This is a key requirement for Kalman filter tracking. If the errors are not known, defaults must be used, which may degrade the track quality and therefore overall system performance.

If in addition to sensor measurement errors there are alignments errors which are not well understood and not corrected the track quality would deteriorate further. Hence reliable alignment techniques are necessary to ensure satisfactory system performance.

The performance of data alignment techniques depends on the mission and performance requirements of the CCS, the data rates and the precision of the equipment within the combat system, and the computer resource limitations. If the precision of the equipment is low, for example, the systematic errors could be large enough to make a very precise alignment algorithm ineffective.

For time alignment, extended Kalman Filtering techniques are used to propagate the measurements to fusion time and to account for uncertainties about the time origin of the measurements.

Martin P. Dana in [Bar-Shalom, 1989, ch. 5] defines the space alignment (registration) of multiple radars as the process of ensuring the requisite "error free" (or more precisely controlled error) coordinate conversion of radar data. This is done by expressing the radar data in a common coordinate system, in which the errors due to site uncertainties, antenna orientation, and improper calibration of range and time have been minimized so they do not cause a significant degradation of the system operation.

In general, to correct for any spatial alignment problem between two sensors, measurements from common firm tracks/contacts are used in different least-squared estimation techniques to evaluate bias and bias covariance values. These values are used to perform a reference frame conversion of all measurements into a common reference frame. The estimation technique used depends on the type of spatial alignment problem, type and frequency of the sensor measurements, and performance requirements and availability of the computer resources.

Specific techniques used to correct specific alignment problems are discussed in the following section.

II.2.4.2.1 Data Alignment on CPF

All three types of alignment problems are encountered on CPF. Certain techniques are used on CPF to correct for alignment errors. Although CPF does not include a data fusion function, the CPF missions and equipment precision are not the same as for the AAW frigate, and the problem is not sufficiently discussed in the literature, some qualitative conclusions can be made about the expected impact of different alignment problems on the AAW frigate performance based on CPF experience.

Time Alignment :

Time alignment is performed in a number of places within the CCS functions:

1. When a sensor stops reporting a target due to EMCON, target moving out of the sensor tracking sectors, malfunction, etc., the CCS software continues to extrapolate the kinematic variables of the target in the system database for a specified amount of time. This is done to allow for it to be correlated with the new data (possibly from another sensor) when it is detected again. By doing this, the historical information collected about the target is preserved.

2. When the operator evaluates from the sensor video display that there could be a target at some position even if the sensor tracking algorithms have not yet reported a track, a new manual track may be entered, and an algorithm called "dead reckoning" is used be CCS to estimate the kinematical variables of this suspected track based on operator manual updates and to extrapolate it. This is done until it is either correlated with a new report from the sensors, or confirmed as non-existing. This enables the CCS software to initiate analysis against a suspected target.

3. On CPF each sensor system includes correlation algorithms which correlate the sensor detected track data with the system database data. These correlation algorithms first extrapolate the system track kinematic variables to the time of detection. This ensures that the correlated tracks are of the same time origin.

Spatial Alignment within the Same Platform:

Spatial alignment on CPF is achieved by first following very precise physical alignment procedures during the equipment installation, and then performing periodic fault isolation procedures to detect and then correct any misalignments during the ship's operation.

The spatial alignment on CPF is considered corrective maintenance. The CCS software includes a maintenance function which provides for many different kinds of automatic and operator requested fault isolation and correction capabilities. Spatial alignment is one of the operator requested maintenance capabilities. This capability is only initiated if the operator suspects misalignment between two sensors while reviewing the tactical situation for tracking. In this case, the operator selects up to three common targets, and the alignment maintenance capability uses the sensor track reports for these targets to compute the bias and the bias error between the two sensors. The bias and the bias error is then used by CCS to perform the coordinate conversion of the track data.

Multi-Platform Spatial Alignment (Gridlocking):

For multi-platform spatial alignment, again a common target is selected reported by ownship and another platform, and bias and bias errors are computed from the kinematic data obtained from both ships (reporting units, as called on CPF). This bias (or gridlock pads, as called on CPF) is used to correct for all data coming from that remote platform. This alignment principally corrects for position errors of the reporting units. On CPF gridlocking can be automatic or manual. In the case of automatic gridlocking, the bias values are recalculated each time the remote platform reports on the common selected track. In the case of manual gridlocking, the bias values are recalculated only upon operator request.

II.2.4.3 The Effects of Misalignment on the Performance of the Data Association and Data Fusion

As already stated, in the MSDF function, before data association, data fusion and state estimation can be performed, all data must be aligned to respect the same reference frame and time origin.

The effect of misalignment on the association process is easy to demonstrate. As discussed in section II.2.2 (Data Association), to evaluate if the measurements/tracks from two sensors associate with each other (or if a measurement/track associates with the central track data in the MSDF database), a gate test is performed comparing the kinematic variables of the measurements/tracks involved in the test. If all the data used in the test does not respect the same reference frame and time origin, the distance between the kinematic variables measured for the same object by two different sensors (or measured by a sensor and estimated in the MSDF database) may fall outside the gate size. Hence the data from these sensors will not associate, and two tracks will be entered in the database instead of one (i.e., this will increase the probability of false alarm). In the case when there are many similar (in terms of category and identification) objects close to each other, this will also cause false associations. Increasing the gate size to account for the error due to misalignment and to ensure association of kinematic variables from the same object is equivalent to decreasing the accuracy of these kinematic variables, and again this may increase false associations.

The kinematic variables of the associated measurements/tracks are ultimately fused to derive the kinematic variables and covariance of the combined track. It is clear from the discussion of the effects of misalignment on the association process that as the probability of false alarm increases, the accuracy of the kinematic variable is decreased or the probability of misassociations is increased, and since this will result in fusing kinematic variables with larger errors or for two different targets, the accuracy of the fused track will be degraded.

Martin P. Dana in [Bar-Shalom, 1989, ch. 5] confirms this analysis for the case of radar tracking within a multi-platform fusion system. The biases or registration errors in plot (measurement) data would degrade system track accuracy if used to update a system track. In the context of a multiple radar tracking system, the presence of registration errors will result in a track mean square error (MSE) larger than that which should be achievable theoretically. If the registration errors are sufficiently large, then multiple radar tracking will be less accurate than single radar tracking. In the worst case, registration errors can result in a failure to correlate multiple radar measurements from a common aircraft with a common track, either reducing the system 'de facto' to a single radar system or even leading to multiple tracks for the same aircraft. Because the fundamental objective of multiple radar tracking is to ensure track continuity for an aircraft as it moves through multiple radar coverage envelopes, registration errors can defeat the very purpose of a multiple radar system.

II.2.4.4 Time Alignment Problems

The timing of measurements to maintain high accuracy and the existence of intersensor misalignments pose significant problems in the development of simplified MSI (MSDF in the context of the AAW frigate) algorithms [Bowman, 1979].

As already stated, there are time alignment problems of the following types:

- different data rate
- out of sequence measurements
- synchronization
- interpolation
- extrapolation
- buffering
- time latency
- bias error (sensor clock time).

The items in this list have been referred to as time alignment problems. However, they are really different conditions when a time alignment is required. Under these conditions different measurements from different sensors for a given target will have different time origin. A short description of each one of these problems is given below:

Different Data Rate:

Sensors within a platform do not usually have the same data rate. Hence for a given target, the data provided by a sensor with a slower rate is usually of an earlier time origin than the data provided by a sensor with a faster rate.

Out of Sequence Measurements:

Out of sequence measurement problems happen when sensor data arrives at the fusion centre in random sequence due to different sensor characteristics and random delays.

Synchronization:

Synchronization of the sensors means that the sensor data for a given target from every sensor arrives at the fusion centre at the same time. It would be very difficult to ensure sensor synchronization even for an operational system with sensors having the same data rate. This would mean that all sensors were activated at the same instant and no communication errors occurred.

Interpolation:

Interpolation is when the measurement time of origin for a given target is of a later time than the time of fusion centre.

Extrapolation:

Extrapolation is when the measurement time of origin for a given target is of an earlier time than the time of fusion.

Buffering:

Buffering is done to reduce communication costs. All measurements by the sensor within the scan are saved in a buffer and transmitted to the fusion centre once every scan. Some of the data in this buffer is of a earlier time origin than others.

Time Latency:

Time latency is when for a given target, the data for an earlier time origin arrives at the fusion centre after data of a later time origin is already received from another sensor.

Bias Error (Sensor Clock Time):

Bias error occurs due to an error in the sensor clock time. Hence the time required for the sensor signal to reach the target and return to the sensor is translated incorrectly, causing an error in range and bearing.

Not all of these alignment problems are addressed in the surveyed literature. [Thomopoulos and Zhang, 1988A] derive filtering algorithms in the case of channel errors and transmission delays and [Thomopoulos and Zhang, 1988B] derive filtering algorithms in the case of uncertainties in the sampling times and transmission delays in a sensor-level architecture. These errors result in similar time alignment problems such as different data rate, out of sequence measurements, synchronization, time latency and buffering. However the performance of these algorithms is evaluated for the very special case of three identical sensors. [Fritz, 1989] describes a fusion system fusing both measurement and track data which considers extrapolation, interpolation and time latency. However the algorithms are not included. No analysis is found for bias error. However it can be corrected in the same way as a spatial alignment problem since it results in a range and bearing error. More detailed discussions of these three studies is given below.

II.2.4.4.1 Analyses of Time Alignment Problems

1. The effects of transmission delay and channel errors on the performance of a distributed fusion system is studied in [Thomopoulos and Zhang, 1988A]. The objective of the study is to investigate how the networking parameters (the probability $\mathbf{p}^i$ that decision of i-th sensor is available at the time of fusion and the probability $\mathbf{p}^{ci}$ of channel i being in error) affect the performance of the distributed decision fusion system, and derive the optimal test that maximizes the probability of detection at the fusion centre for a fixed probability of false alarm. This study

presents the following derivations:

a. Optimal Fusion Rule with delays and ideal channels

b. Optimal Fusion Rule with noisy channels

c. Optimal Fusion Rule with delays and noisy channels

d. Suboptimal Solution, a near-to-optimal algorithm to solve for the sensor and fusion thresholds sequentially.

Performance evaluation is done for a distributed fusion system with three sensors. For numerical convenience and for the sake of presentation clarity, it was assumed that all of the three sensors incurred the same networking delays, i.e., that during a fusion interval, they transmit their decisions to the fusion centre with the same probability. Furthermore, and for the same reasons, it was assumed that the error probabilities in the different channels over which the sensors transmit their decision to the fusion were the same.

Evaluation results are presented for different networking parameters and for different fusion centre combining policies, e.g., when more than one peripheral decision is received, the fusion centre can choose either OR or AND policy. The following conclusions were made:

a. The OR policy yields best performance.

b. The performance of the sequential solution is very close to the optimal solution in the case of the OR policy.

c. In every policy, the performance of the system decreases and the probability of channel errors and delays increases.

2. The problem of estimation and control with distributed sensors in the presence of delays in the transmission of both information and control signals has been considered in [Thomopoulos and Zhang, 1988B], where the minimum mean squared error filter and the optimal quadratic cost controller are derived in the presence of transmission delay and uncertainty in the sampling times. The sensors obtain measurements about target trajectories at random times, which they transmit to the fusion centre. The measurements arrive at the fusion with random delays which are due to queuing delays and random delays in the transition time as well as in the propagation time (sensor position may be unknown or changing with respect to the fusion). The fusion generates estimates of the target tracks using the received measurements (not processed track states). The

measurements are received from the sensors at random times, may have unknown time origin and may arrive out of sequence. It is shown that the optimal filter for the estimation problem of target tracks based on measurements of uncertain origin received by the fusion at random times and out of sequence is an extension to the Kalman Filter to account for the uncertainty involved with the data time origin. The serial filter is derived for:

a. Random Sampling and Fixed Delay

b. Fixed Sampling and Random Delay

c. Random Sampling and Random Delay. (This is non-realizable. Hence the Fixed Sampling and Random Delay filter is used where the sampling time of every measurement is set equal to its conditional a-posteriori mean.)

The simulation of Random Sampling and Random Delay is not presented. The results of the Random Sampling and Fixed Delay and Fixed Sampling and Random Delay are as follows:

a. Comparison of serial Kalman Filter with the parallel one indicates that the serial yields superior results.

b. The randomness due to either sampling or delay degrades the performance of the filters.

c. Although the dynamics of the state equations are stationary, the covariance matrix does not reach a steady state due to the time variations in the observation model that are introduced by the uncertainty in the sampling time or/and the transmission delay.

d. Random delays yield larger error covariance, i.e., they have a more negative effect on the quality of the filter than random sampling with fixed delays.

3. [Fritz, 1989] discusses the P-3 Update IV avionics system automated Multi-Sensor Track (MST) algorithms. One of the key features of the MST design are provisions to accommodate time-late data. Propagation (extrapolation) of the state and covariances is first performed to produce predictions of the pair at a common time point.

   Since differing measurement and communication delays can lead to late data, i.e., measurement updates that arrive after another sensor has already updated the track to a later time, late measurements are processed by letting the Kalman Filter measurement function be the prediction of the earlier measurement as a function of the late state. This processing is equivalent to propagating the state and covariance, without process noise, back to the late measurement time point (interpolation), performing an ordinary measurement update, and then propagating back to the original time point, again without process noise. Since process noise is not included in the update, a late-time cutoff is imposed beyond which the late data is not processed.

II.2.4.5 Spatial Alignment Probiems Within the Same Platform

The spatial alignment problems within the same platform are best explained in [Bowman, 1979]. In this study the relative sensor misalignments are separated into three types:

- parallax error
- base-to-base alignment (random error alignment, for the context of the AAW frigate)
- line-of-sight (LOS)-to-base alignment (bias error alignment, for the context of the AAW frigate).

Parallax error is due to the translational displacements of the sensors and depends on the threat location. Thus, the determination of parallax error involves the rough modelling of target motion and the computation of trigonometric functions. Such computations can be performed in real-time but require dedicated hardware (or firmware). Additional parallax errors due to error in the estimate of target motion and linear motion of the sensors are negligible [Bowman, 1979].

Base-to-base misalignments are caused by the dynamic flexure and vibration of the platform. To solve for these alignments, in this study internal measurement units (IMUs) are attached to the base of the sensors. The relative coordinate alignments are then obtained by comparing the IMU outputs. Since unsatisfactory errors usually result from unmodified gimbal matching, and since direct methods such as using (optical) collimators are operationally undesirable due to implementation considerations, an indirect approach such as acceleration and angular rate (vector) matching remains. The high frequency computational burden of this last method can be reduced by performing a position match at a slower rate and trading off "observability" of the alignment [Bowman, 1979].

LOS-to-base misalignments are between the LOS sensor active elements and its base IMU after sensor compensation. Errors in this alignment can be due to the environment, structural flexure and vibration, and the accuracy of the sensor resolvers. The relative residual misalignments between the sensor reception elements after the principal sources of misalignment (including measured parallax, base-to-base, and LOS-to-base alignment corrections) are removed can be estimated by the integration of the sensor track data. This integral relative residual misalignment estimate, especially of bias-type errors, among sensors and between sensors and weapon improves system sensor cuing and handover capabilities as well as improving overall accuracy [Bowman, 1979].

The modelling of the residual relative misalignment errors in an operational system will depend on methods used to compensate for the three principal sources of misalignment. For now, these residual misalignments are modeled as a bias plus random noise in special coordinates. This model is chosen for its ease of implementation in real-time code [Bowman, 1979].

The Maximum Likelihood analysis with alignment considerations and the Kalman filter algorithm that considered the alignment derivations are also included in the paper.

There are other studies that have also investigated spatial alignment problems and different ways to account for them [Wax, 1983; Beaulieu, 1985; Lee and Van Fleet, 1989; Shoults, Simmons and Ruo, 1990]. Although these studies may not all be directly applicable to the AAW frigate implementation, they are useful as examples of different methods of correcting these problems. The conclusion from these studies is that there are two different approaches for spatial alignment within the same platform:

1. Take into account the alignment errors in the state estimation Kalman filter, conducting smoothing over local random track errors and random intersensor misalignments as in [Bowman, 1979; Wax, 1983].

2. Use filtering techniques to estimate the alignment error as in [Beaulieu, 1985; Lee and Van Fleet, 1989; Shoults, Simmons and Ruo, 1990].

The specific approach taken will depend on the combat system architecture, the performance requirements and the available processing resources.

A summary of the aforementioned studies of spatial alignment problems is given below.

II.2.4.5.1 Other Studies of Spatial Alignment Problems Within the Same Platform

1. [Wax, 1983] derives the Maximum Likelihood estimate of an object position from multiple measurements provided by an array of spatially distributed mixed mode (dissimilar) sensors. The algorithm is derived for the case of small sensor measurement and navigation errors. Small error assumption is valid when a priori reasonably good estimate of the true position of the object is available. When it is not available an iterative solution algorithm is derived. The study observes that the convergence of the iterative method is not generally guaranteed. However, for the range-only system the algorithm converges to the correct solution.

   The study explains that comparison of the algorithms of this study with those of previous studies derived for special cases (e.g., range-only, bearing-only, no navigation errors) concludes identical results in both small error and iterative algorithms.

The algorithms in this study are applicable both for the alignment of sensors on the same platform (when navigation errors are equal to zero) and for multi-platform alignment.

2. [Beaulieu, 1985] discusses a technique for alignment of the Electro-Optic Tracker (EOT) and SAR-8. Possible errors that are expected when fusing EOT and SAR-8 are: (1) Pixel size; (2) Azimuth reference synchro, which is used to determine LOS azimuth with respect to the beam of the ship. This error varies cyclically in one revolution of the synchro and could be corrected for as it is a function of shaft position; (3) Determination of roll and pitch angles obtained from the stabilized platform synchros. Also, the stabilized platform can be off the horizontal plane; (4) Platform stabilization, which is not easily predictable because it depends on previous history of roll and pitch as well as wings and ship manoeuvres. This error could probably be evaluated from the error signals of the vertical gyros used for stabilizing the platform, but these error signals are not readily available and will not be considered; (5) Tracking algorithm approximation; (6) Converting the target coordinates into True North inertial frame of reference; (7) Since SAR-8 and EOT are not co-located there will be further errors due to bending and twisting of structures; (8) Computational precision; (9) Yaw synchro error; (10) The Delay in inputs, etc.

   The fundamental technique of the alignment involves tracking of a target independently. This simple alignment technique would consist of estimating the difference in azimuth and elevation for four different azimuth quadrant sectors used for zeroing the horizontal and vertical offsets as well as the tilt offset of the EOT platform in a slow but continuous fashion. By increasing the number of memory cells, it is possible to have an alignment correction for synchro nonlinearity (systematic errors due to electromechanical distortions or imperfections).

   Due to the separation between the SAR-8 and EOT, the parallax angle will vary with range. An approximate value is taken. Although the total error is taken as the sum of all, it is exaggerated since the errors do not happen at the same time and under the same conditions.

3. [Lee and Van Fleet, 1989] present an approach to estimate and minimize registration error between an optical or infra-red imaging and a non-imaging radar. Registration between two sensors is the process of matching two sensor coordinate systems through a transformation to a common coordinate system and determining the relative offset (bias) between the two. The offset information provides information concerning the position of one sensor measurement relative to the position of the other. Since the measurements are never free of noise, a statistical method is needed to obtain an estimate of the true offset and the estimation error. As the two signals from each sensor are quite different and there is no common feature that can be matched, the calculated centroids of objects are used as the registration control point in this effort. Given

the centroids, the registration method is independent of the sensors involved.

The paper introduces a centroid estimation error model in an imaging sensor and in a nonimaging radar. The estimated centroids and the variance of the total noise are used to estimate and minimize the relative registration error between the infra-red imaging sensor and nonimaging monopulse radar.

The optimal range that minimizes the mean square registration error is obtained by finding the range for which the first derivatives with respect to the range of the mean square registration errors for azimuth and elevation axes are zero.

It is assumed that the two sensors are co-located on a common gimbal so that there is no parallax error. (When the two sensors are not co-located, the parallax error can be easily calculated from the distance between the two sensors and the range can be adjusted.)

4. [Shoults, Simmons and Ruo, 1990] address an automatic sensor alignment (AUTOLIGN) technique which implements a Kalman filter in the aircraft's onboard computer to provide an automatic estimate of sensor misalignments just prior to each aircraft mission. This technique uses an alignment accelerometer module (AAM) mounted to each avionic/weapon subsystem to provide continuous data to the AUTOLIGN estimator (accelerometers measure the force that the aircraft structure imparts on the instrument to resist gravity, or the force that the structure exerts on the instrument as the aircraft accelerates). Accelerometers in an Internal Measurement Unit (IMU) define an orthogonal coordinate system which is fixed to the aircraft body and is taken as the reference coordinate system. The equivalence of the specific force vectors is used to compute the transformation (misalignment) between the sensor (AAM) and reference (IMU) frames.

II.2.4.6 Multi-Platform Spatial Alignment Problems

In the surveyed literature multi-platform spatial alignment problems are analyzed the most. This is due to the fact that multi-platform alignment became a requirement much earlier than alignment for sensors on the same platform.

The earliest air search radar integration process was developed more than 40 years ago. The development of SAGE procedure in the years following World War II provided the first opportunity to merge automatic computing technology with radar data. Today's version of SAGE procedure for multisensor registration was adopted by the US Navy for use in the Naval Tactical Data System

(NTDS), which is an automated system for the netting of surveillance data and dissemination of tactical command and control information employed on most larger Naval combat vessels. Over the 20 years in which NTDS has been operational the registration software has improved considerably through a sequence of gridlocking algorithms and associated algorithms for the alignment of data from multiple radars on the same platform. Overall registration accuracy is still only in the order of a mile or so [Fisher, Muehe and Cameron, 1980].

As already explained, the multi-platform registration comprises a set of algorithms that use measurements for common targets tracked by two platforms (targets of opportunity).

The registration process must transform position data on all targets and tracks to a form suitable for input to each tracking process. To be consistent with the tactical situation, registration should be a continuing process. Upon initial setup of a network of radar sites, the registration process should automatically begin to tie the data from those sites together by appropriate adjustment of site parameters based entirely on data derived from targets of opportunity [Fisher, Muehe and Cameron, 1980].

In the automatic registration (gridlocking) process the registration/navigation errors and biases are estimated in real time by the comparison of coordinates of associated tracks from different sights. A linearized or extended Kalman filter is typically used to estimate the biases [Bath, 1982].

The heart of any registration process in an understanding of the mechanisms by which various error sources contribute to total registration error. Possible sources of registration problems between two radars are given in Table II.1 [Fisher, Muehe and Cameron, 1980].

Table II.1. Sensor Registration Sources of Error

SENSOR REGISTRATION, SOURCES OF ERROR	
SOURCE	CORRECTIVE MEASURES
RANGE:	
OFFSET	CALIBRATE AT FACTORY
RANGE SCALE	ACCURATE RANGE CLOCK
ATMOSPHERIC CORRECTION	TABULAR CORRECTION
HEIGHT CORRECTION	3D RADAR OR OTHER SOURCES OF HEIGHT INFO (e.g. MODE 3)
AZIMUTH:	
OFFSET	NORTH-SEEKING GYRO
ANTENNA TILT	AUTOMATIC TILT MEASURING SYSTEM
TIME:	
OFFSET	TIMING CORRECTIONS PROVIDED BY COMMUNICATIONS SYSTEMS
TIME SCALE	ACCURATE CLOCKS
RADAR LOCATION:	
LATITUDE, LONGITUDE, HEIGHT	ACCURATE NAVIGATION EQUIPMENT
COORDINATE CONVERSION:	ACCURATE ALGORITHMS

The general outline of the methods and simulation results detailed in [Fisher, Muehe and Cameron, 1980; Bath, 1982; Feldman, 1988; Bar-Shalom, 1989, ch 5] are given below.

II.2.4.6.1 Studies of Multi-Platform Spatial Alignment Problems

1. [Fisher, Muehe and Cameron, 1980] develop a self-registration algorithm which automatically brings each sensor into registration with the remainder of the network whenever its situation is

changed. The registration process assumes that all errors are initially minimized by installation and calibration, and uses targets of opportunity to estimate a set of bias error corrections. To minimize coordinate conversion errors (compared to errors due to traditional approximations) a geodetic coordinate system was selected for data reporting. The steps performed by the self-registration algorithm are:

1. smoothing and coordinating the timing of the target reports from each sensor to generate a smaller set of reports (referred to as "superpoints")

2. adjusting the superpoints to account for known biases

3. correcting the superpoint ranges for atmospheric refraction

4. computing the covariance matrix of the position differences as observed by the two radars for each superpoint

5. solving for the set of bias components using a maximum likelihood approach

6. estimating the variances of the biases.

Step (5), being iterative, is the least straightforward and most computationally demanding of the six. It involves minimizing a function **S** which is the sum of squares of the residual vectors (difference in position measurements, or bias parameters) scaled to take into account the orientation of the combined measurement error ellipse [Fisher, Muehe and Cameron, 1980]. Three alternative approaches are suggested for minimization of **S**: (1) the generalized linear least squared estimation (GLSE) technique, (2) the grid search technique, where **S** in minimized in each bias parameter separately, (3) Powell's method for steepest decent. The (1) approach was rejected due to high computational demands, (2) was rejected due to slow convergence. The third approach is selected due to its fast convergence. The details of this method are given in the study. It is an iterative method where conjugate vectors are established in each minimization of **S**. **S** is minimized along the new conjugate direction and the obtained bias vector is used in minimization of **S** to establish new conjugate vectors.

The study includes algorithms for the coordinate conversion, and for the steps identified above for two sensors. The self-registration algorithm was tested by analyzing both simulated and real data from two sensors spaced about 45 nautical miles (nmi) apart. The results demonstrated the essential accuracy of the algorithm and provided final rms registration accuracies of about one milliradian in azimuth and 20 meters in range, which is about twice the measurement accuracies of the individual sensors.

2. [Bath, 1982] discusses a technique for associating two or more moving platforms in the presence of very large navigation errors and sensor misalignments. Track association is complicated by site registration or platform navigation errors and by biases in the radar measurements (e.g., North misalignments). These errors and biases can prevent association of tracks which do not correspond to the same target and prevent association of tracks corresponding to different tracks. The radar track association algorithms developed in the study can operate reliably even in the presence of large unknown registration/navigation errors and radar biases.

   In principle, automatic registration eliminates the registration/navigation errors and the radar biases. However automatic registration algorithms presuppose the existence of correctly associated track pairs whose coordinates can be compared. Thus the problem of track association in the presence of large registration/navigation errors and radar biases must still be solved prior to automatic site registration.

   A practical approach to association with large navigation and alignment errors is to cross-correlate the two entire track files (local and remote). Consider two track bases with some fraction of the tracks held in common. By properly rotating and translating one track base, the two pictures can be made to coincide. The three largest errors will be assumed to occur in latitude, longitude and azimuth alignment. It can be shown that if a remote track base, misaligned in azimuth, is transformed into the local coordinate frame using incorrect latitude and longitude (but using the exact curved Earth equations), then this transformed track base and the local track base can be very nearly lined up by a simple horizontal plane translation and horizontal plane rotation. The cross-correlation approach is, then, directly applicable to actual navigation and navigation errors, provided it is extended to include a horizontal plane rotation as well as translation. Velocity and altitude data can be used to make the real pairing spike more visible in the background of random association pairs.

   The cross-correlation hypothesis test with three unknown parameters x translation, y translation and azimuth rotation is performed. The contribution of each possible local-remote track pair is then weighted by the pair's velocity and altitude likelihood ratios.

   The association process, in the presence of large navigation errors and misalignments, can be summarized as follows:

   1. Compute the three dimensional cross-correlation array using the local and remote local databases.

   2. Find the "centre of mass" (the composite spike corresponding to the collection of real pairings) in the cross-correlation array. (This will be referred to as the cluster point.)

3. Select the track pairs at (and in the near vicinity of) the cluster point as the associated pairs.

Simulation result show that this process is effective even when the number of common tracks is small (e.g., two or three).

3. [Feldman, 1988] describes the U.S. Navy's Advanced Combat Direction System (ACDS) Block 1 track management function which includes algorithms for bias evaluation, estimation of inter-sensor bias like that between ownship ESM and radar, and gridlock correction.

The automatic ongoing gridlock correction process accounts for remote/local misalignment in x, y, azimuth and range scale which was induced by biases in navigation system estimation of ownship position and radar tracking biases. The process corrects for misalignment with the Link 11 Gridlock Reference Unit and for misalignment with each Link 16 participant (Link 16 has no GRU). A least mean squares batch processed gridlock correction algorithm is used which requires less computer processing (CPU time) than a Kalman filter approach with comparable bias reduction performance.

To evaluate combined remote/local correlation algorithm and gridlock performance and refine the algorithms, a system model was developed that simulates sensors, data link, and Block 1 track management. The results show excellent gridlock quality over the scenario life. The simulated correlation outperforms the requirements for % DD (remote-local dual designations) and % FC (false correlations). For at-sea performance ID and IFF responses will also be available to aid correlation.

4. A Martin P. Dana article included in [Bar-Shalom, 1989, ch. 5] describes the theory for performing registration, bias estimation and covariance analysis when tracking with radars on different platforms.

The paper summarizes different bias estimation techniques in [Wax, 1983] and [Fisher, Muehe and Cameron, 1980]. It also presents simulation results which were mainly aimed at comparing different GLSE methods with other methods and determining the sensitivity of selected registration techniques to the assumptions of the techniques. The results show that for current technological capabilities the computational demands of GLSE are modest, and that GLSE outperforms the other methods in terms of registration accuracy and stability (less sensitive to sensor and target geometry). The GLSE algorithms can achieve satisfactory registration accuracies with 50 to 100 point-pair rather than the 200 often required by existing registration algorithms.

II.2.4.6.2 The Impact of the Earth's Curvature

In all the above studies the conversion into the common coordinate system is done before the bias and the bias covariance are estimated. In most of the studies it is stated that conversions are performed using the exact curved Earth equations. However, none of the studies provide an evaluation of the impact on the bias estimation process if the flat Earth approximation is used. The errors in kinematic variables due to flat Earth approximation instead of curved Earth equations are the following:

1. Both platform coordinate systems are with respect to true North. Hence in the curved Earth equations, rotation as well as translation is required, while in the flat Earth approximation, only translation is performed (illustrated in Figure II.9a).
2. The aircraft height measured by ownship and by a remote platform would be different if Earth curvature is not taken into account (illustrated in Figure II.9b).
3. The distance between the two platforms in the flat Earth approximation is different from the true distance in the curved Earth equations (illustrated in Figure II.9a).

The error due to the flat Earth approximation depends on the distance of the target as well as the distance between the platforms. The impact of this error on the performance also depends on the precision of the sensors on the two platforms.

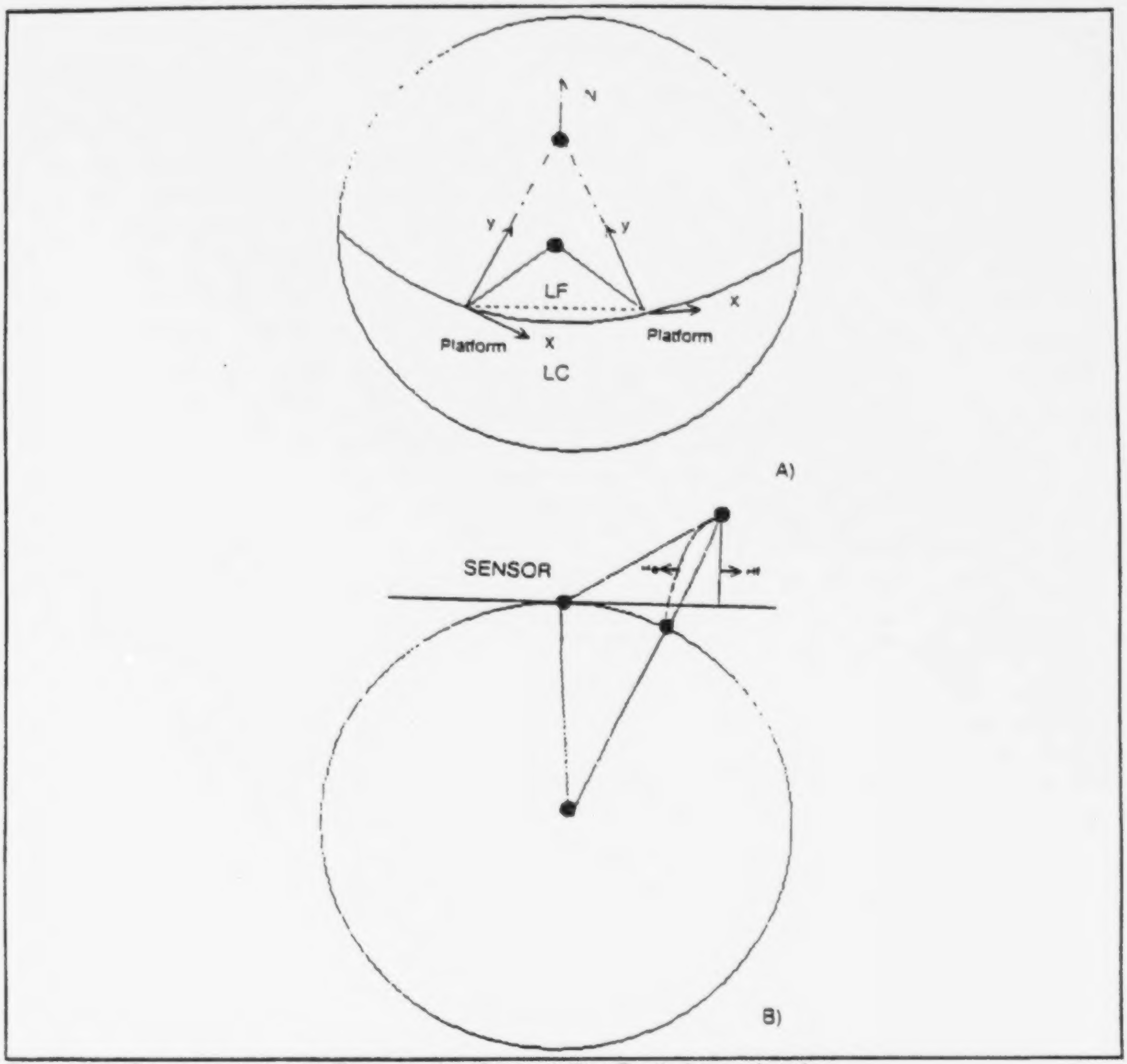
z
y
y
LF
x
Platform
x
Platform
LC
A)
SENSOR
B)

Figure II.9. Range and Height Errors in the Case of Flat Earth Approximation

II.2.5 Target Attribute Estimation/Fusion Analysis

II.2.5.1 Introduction

The role of the target attribute estimation and fusion process is to provide the necessary algebra in order to manipulate the evidence and extract the identity of the target under tracking with an appropriate level of confidence. For the target identification task to profit from the synergy created by the fusion of multiple sensor data, all sensors should provide some attribute information. The level of such information is not the same for all sensors. The IFF provides attribute information that indicates if the target has "responded" or "not responded" to the interrogation. The ESM sensor is typically oriented for deriving attribute information. It can provide different types of data about the radar used by the target platform such as the frequency (F), pulse repetition frequency (PRF), pulse width (PW), beam width (BW), etc..., or data on any other emitting device like radio, beacon etc... Depending on the measurement processing capability, one or more candidate target types can be inferred from these emitter attributes. The radars of today as well as the IRST do not provide attribute information. Future developments will probably permit the extraction of attribute information obtained from the modelization of the measured radar cross section (RCS) as a function of the aspect angle or from the infra-red spectrum signature.

This section uses terminology which is used differently in some other publications. To avoid confusion, the definitions of the expressions target type, target attribute and, database requirement used by this study and applied to the target attribute estimation process are presented. Target type stands for the identity of the target. Examples of target type are CF-18 aircraft, harpoon missile, CPF frigate, Boing 747, etc. Target attribute stands for any element or physical characteristic which belongs to a target type. For example, radar cross section, infra-red signature, radar SPS-49, radar Sea Giraffe, etc. Usually many attributes are necessary to establish the target type. Database requirement stands for the contents of the threat library. The contents are a function of the method used to correlate the evidence. This specific subject will be discussed in section III.2.5.

The first implementation issue to analyze is related to the choice of the selected fusion architecture. A sensor-level fusion system will combine the sensor reported target type hypothesis. The estimated identity will be selected by the attribute estimation process from the suggestions of all sensors. Each sensor will have its own threat library specifically tailored to the kind of attribute it measures. A central-level approach will fuse attributes from all sensors and select candidate identity directly from the attributes. The central-level approach (also called attribute level) is theoretically more accurate [Blackman and Broida; 1990] but requires massive calculations. The sensor level approach exploits the parallelism which reduces the time required to obtain the identification, but the inference to a wrong identification is more likely to happen as happens in the central approach.

II.2.5.2 Methods to Correlate Evidence

Typical attribute data are not variable on a continuum as are the positional data, but are subjective information to which a probability value or a level of confidence is assigned. This kind of data is called evidence. A precise and unique formalism to systematically solve the attribute fusion problem does not exist. Present methods such as voting approach and possibility theory are simple to implement but suffer from consistency problems in arriving at an optimal solution [Hall and Linn, 1987]. The following paragraphs discuss the most popular methods to correlate evidence. Other methods are mentioned and outlined in [Waltz and Llinas, 1990 ch. 7].

II.2.5.2.1 Voting Schemes

This method is briefly discussed in [Waltz and Llinas, 1990]. To apply this technique each sensor sends an attribute declaration for a target being tracked. The declaration is set according to rules, internal to each sensor. Each time an element of the database (target type) supports a sensor declaration there is a vote for this element. The selection of the final identity is then obtained from the pluralism, i.e., the target type which receives the most votes from all the participating sensors. For better accuracy the pluralism rule can be changed to a "weighting vote rule", which multiplies the votes of some sensors by an integer, larger than one, related to the quality of the sensor. An application of this method is incorporated in the next paragraph.

II.2.5.2.2 Possibility Theory

The idee of this method are outlined in [Blackman and Broida; 1990], more details can be found in [Ruspini, 1982]. The main essence of this method is to arrive at the identity through a process of elimination. At a starting point all target types are considered as potential candidates and receive a possibility value of one. The sensors send reports which contain attribute declarations with a supporting confidence level. As sensor attributes are sent, the possibility value is updated. Let $P(A_i)$ be the possibility of the target type A_i and C_j be the confidence level for a measured attribute j. If the target A_i supports the declaration of the sensor, then the possibility value stays unchanged. If the target does not support the observation then, the update of the new possibility value is:

$$P_{new}(A_i) = P_{old}(A_i)\,[1 - C_j] \tag{II.37}$$

The decision rule to keep or withdraw is taken from the utilization of certain threshold parameters. In a general application, two thresholds T_a and T_r can be used with the following decisions rule:

$$\begin{array}{ll} \textit{Identification accepted if} & P_{new} > T_a \\ \textit{Identification hold if} & T_r \leq P_{new} \leq T_a \\ \textit{Identification rejected if} & P_{new} < T_r \end{array} \qquad \text{(II.38)}$$

The following example sketches the major technical aspects of the voting and possibility method. Table II.2 presents a database example which is a small threat library. This database contains only five target types, each with five corresponding attributes. The letters H and F stand for hostile and friend, the rest of the information is given under an arbitrary numeral index related to the type of equipment and or some physical characteristics of the targets.

Table II.2. Example of Threat Library Database Information

	IFF	Radar Type	Nav. Radar type	RCS Code	IR Spect. Code
A_1	H	2	1	5	7
A_2	H	3	3	5	8
A_3	H	4	2	4	8
A_4	F	1	1	1	1
A_5	F	3	2	6	8

Table II.3 represents typical output from four sensors. The output includes the attribute declaration and a confidence level associated with the measurement of the attribute. As shown by the ESM radar attributes, the declarations can be multiple. The last column represents the attribute index which is necessary due to the recursive nature of equation (II.37).

Table II.3. Typical Output From Four Sensors

	Attribute Declaration	Confidence	J
IFF	Responded Friend	0.55	1
ESM	Radar Type 3 or 4	0.75	2
	Nav. Radar Type 2	0.85	3
IRST	Spectrum 8	0.50	4
MRR	RCS 4	0.03	5

Table II.4 shows the possibility values obtained from the application of equation (II.37) as a function of the attribute index. The row where j=0 represents the starting step. To illustrate the multiple declaration possibility, ESM has declared that one of two types of radar correlate to the observations. Each time an attribute observation from Table II.3 supports a corresponding element from the database the possibility variable is unchanged. When all attribute data has been covered the attribute estimation process is ready to eliminate the unlikely candidates. If the thresholds T_a and T_r are set to 95% and 10% respectively the target types A_1, A_2 and A_4 are rejected and the target A_5 is suggested as the candidate identity. Ambiguity persisting since A_3 is still maintained without being eliminated.

Table II.4. Possibility Values as a Function of Attribute Index

J	A_1	A_2	A_3	A_4	A_5
0	1	1	1	1	1
1	0.45	0.45	0.45	1	1
2	0.1125	0.45	0.45	0.25	1
3	0.0169	0.0675	0.45	0.0375	1
4	0.0084	0.0675	0.45	0.0188	1
5	0.0082	0.0655	0.45	0.0182	0.97
Decision	Rejected	Rejected	Hold	Rejected	Accepted

Table II.5 shows the results of the voting approach on the same scenario. Each time an attribute observation from Table II.3 supports a corresponding element from the database one vote is given to the target type. A simple pluralism rule leads to an ambiguous result since A_3 and A_5 gets the same number of votes.

Table II.5. Results of Voting Approach

J	A_1	A_2	A_3	A_4	A_5
1	0	0	0	1	1
2	0	1	1	0	1
3	0	0	1	0	1
4	0	1	1	0	1
5	0	0	1	0	0
Total vote	0	2	4	1	4

II.2.5.2.3 Bayesian Probability Theory

This approach uses the formalism of the theory of probability. The cornerstone of the technique is the Bayes formula. This formula illustrates the commutativity between two independent random events A and B. If P(A) is the unconditional probability that event A occurs and P(B|A) is the conditional probability that event B occurs knowing that event A has occurred then the Bayes rule states:

$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)} \qquad \text{(II.39)}$$

Here the probabilistic formalism is applied to the target identification problem in the context of multiple sensors with time sequential data. Application of probability to the problem of target identification was first studied by [Shulman, 1978] and is discussed exhaustively by [Nahin and Pokosky, 1980].

In the scenario depicted in Table II.3, ESM declares that only navigation radar type 2 supports the measured data to a level of confidence of 85%. The other 15% of the confidence is shared by the other types of navigation radars (here it is assumed that ESM can always discriminate between navigation radar and other radars, which is not necessarily the case in real situations). If the database indicates that the only other navigation radar types are 1 and 3, it is possible that in the same circumstance a type 1 would have been declared when in fact type 2 was present due to the uncertainty in the measurements. Before ESM receives any data there is some probability that types 1,2, and 3 are present in the coverage area. This inferred probability is called the "a priori" probability. From the starting knowledge of this a priori probability, and the confidence level in the first declaration, the knowledge of the a priori probability can be readjusted. Again referring to the example above, the purpose is to compute the probability that navigation radar type "i" is really present knowing that ESM declares type "j" to a certain level of confidence. First the following random variables must be clearly defined:

B_i ≡ navigation radar type "i" is present.

β^1 ≡ navigation radar type "j" is declared at time 1.

From analogy with state estimation these variables can be called the estimated and the measured parameters respectively. Now the conditional probability that variable B_i occurs knowing that β^1 has occurred is obtained from the Bayes rules:

$$P(B_i|\beta^1_j) = \frac{P(\beta^1_j|B_i)\,P(B_i)}{P(\beta^1_j)} \qquad \textbf{(II.40)}$$

The unconditional probability in the denominator term is a function of the conditional probabilities that all navigation radar types are present in the covered area. The expression (II.40) is rewritten as

$$P(B_i|\beta^1_j) = \frac{P(\beta^1_j|B_i)\,P(B_i)}{\sum_{s=1}^{3} P(\beta^1_j|B_s)\,P(B_s)} \qquad \textbf{(II.41)}$$

If at a later time 2, ESM makes another declaration β^2_k the unconditional probability that B_i occurs must be assessed taking into account the two measurements. Therefore

$$P(B_i \mid \beta^1_j \cap \beta^2_k) = \frac{P(\beta^1_j \cap \beta^2_k \mid B_i)\,P(B_i)}{P(\beta^1_j \cap \beta^2_k)} \qquad \textbf{(II.42)}$$

Where the symbol $\cap$ stands for intercept or logical "and". If β^1 and β^2 are considered independent the equation (II.42) can be rewritten as:

$$P(B_i \mid \beta^1_j \cap \beta^2_k) = \frac{P(\beta^1_j|B_i)\,P(\beta^2_k|B_i)\,P(B_i)}{P(\beta^1_j)\,P(\beta^2_k)} \qquad \textbf{(II.43)}$$

The unconditional probabilities in the denominator term must be expressed in a sum of conditional probabilities with a special attention to P(β_k^2.

$$P(B_i|\beta_j^1 \cap \beta_k^2) = \frac{P(\beta_k^2|B_i)\,P(\beta_j^1|B_i)\,P(B_i)}{\sum_{s=1}^{3} P(\beta_k^2|B_s)\,P(B_s|\beta_j^1)\sum_{s=1}^{3} P(\beta_j^1|B_s)\,P(B_s)} \qquad \text{(II.44)}$$

Here the recursive nature of the treatment can be noticed. Analogously this treatment can be extended to a time sequence of the ESM report on the navigation radar attribute. To get a recursive equation, some modification to the notation is required:

$\vec{\beta}^n$ ≡ Set all the time sequenced attribute declarations up to time "n".

β^n ≡ Attribute declaration at time "n".

$P(B_i|\beta^0)$ ≡ a priori probability $P(B_i)$ of the starting point.

Using this notation, the bayesian approach to estimating the confidence in the attribute of any sensor is given by:

$$P(B_i|\vec{\beta}^n) = \frac{P(\beta^n|B_i)\,P(B_i|\vec{\beta}^{n-1})}{\sum_{s=1}^{S} P(\beta^n|B_s)\,P(B_s|\vec{\beta}^{n-1})} \qquad \text{(II.45)}$$

where "S" is the number of attribute types that can be declared by the sensor. To apply this equation, the database or the processing system should contain or compute S^2+1 inputs. These inputs are the starting a priori probabilities $P(B_i)$ and all the confidence levels $P(\beta_j|B_i)$ which are usually represented by a square matrix. This matrix, for practical reasons, can be considered as time independent but since the environmental conditions change as a function of time it would be more reliable to use time dependent conditional probabilities.

Table II.6 contains an example of five ESM attribute declarations as a function of time.

Table II.6. Examples of ESM Attribute Declarations

Time	1	2	3	4	5
Nav. Radar Type	3	3	2	3	1

In this example the number of navigation radar types is three, so S=3. The a priori probabilities are considered equal to 1/S for each type (the maximum likelihood a priori choice [Nahin and Pokosky; 1980]). The confidence level matrix is time independent and is:

$$P(\beta_j|B_i) = \begin{pmatrix} 0.75 & 0.10 & 0.15 \\ 0.05 & 0.65 & 0.30 \\ 0.15 & 0.20 & 0.65 \end{pmatrix} \qquad \text{(II.46)}$$

where the "i" index refers to row and "j" index to column. Using the equation (II.45) with n=1 and $\beta^1=3$, the estimated probability that type 1 be present when type 3 is declared, is given by:

$$P(B_1\ present|\beta_3\ declared) = \frac{0.15/3}{0.15/3+0.3/3+0.65/3} \qquad \text{(II.47)}$$

Similarly, the estimated probability that type 2 occurs when type 3 is declared and that type 3 occurs when type 3 is declared is calculated the same way. The answers are 0.136, 0.273 and 0.561 for types 1,2 and 3 respectively. These results are a measure of the probability of presence of each type at measurement time 1. At time 2, the probabilities are recalculated using the previous estimates. For example, with n=2 and $\beta^1=3$, the application of equation (II.45) to B_2 leads to:

$$P(B_2|\beta_3\ ,\ \beta_3) = \frac{0.3(0.273)}{0.15(0.136)+0.3(0.273)+0.65(0.591)} \qquad \text{(II.48)}$$

The answers for each type at every time are presented in Table II.7 below.

Table II.7. Probability of Presence for Each Type at Every Time

Prob. of Presence	Time Sequence of Navigation Radar Declaration					
	Start	3	3,3	3,3,2	3,3,2,3	3,3,2,3,1
type 1	0.333	0.136	0.042	0.007	0.002	0.010
type 2	0.333	0.273	0.168	0.174	0.089	0.032
type 3	0.333	0.591	0.790	0.819	0.909	0.958

The Bayesian approach applied to the attribute level of each sensor data does not automatically lead to target identification. If similar processes are applied to the other sensors the identification target decision will simply be taken from the product of each associated attribute probability of presence.

II.2.5.2.4 Dempster-Shafer Theory of Evidence

The Dempster-Shafer theory of evidence [Shafer, 1982; Strat, 1984] has been identified recently as a powerful approach to solving the problem of target identity [Bogler, 1987 with the comments of Buede, 1989; Dillard, 1982; Garvey, Lowrance and Fischler, 1981] and also to addressing the tracking problem [Betz, 1988].

To apply this method, the sensors should send the conclusions about the measurements they have performed under the form of propositions with a "belief" value associated with each proposition. A proposition can be a simple proposition like "navigation radar is type 3", a combination of exclusive propositions like "navigation radar is type 2 or 3", a combination of nonexclusive proposition like "platform is ship type 2 and aircraft type 2" or the negation of a proposition like "aircraft is not type 2".

The mathematical formalism of the evidence theory requires that propositions be represented by sets of elements. More exactly a proposition is a subset of the set made of all possible irreducible elements which form the "frame of discernment". Table II.2, for example, represents a typical frame of discernment. This set may contain two types of IFF response, seven types of radar, six RCS codes and eight codes of IR signature. Target type A_1 is simply a subset made of certain elements of this larger set. A proposition can also be represented by a more complicated set like the nonexclusive proposition describing a subset made of two smaller subsets.

The belief is a value associated with the proposition which indicates the level of confidence or certainty given by the sensor. There are three fundamental axioms about the belief which form the spine of the evidence theory. Let $b(A_n)$ be the belief in a proposition represented by subset A_n, Θ be the frame of discernment or universal set and $\varnothing$ the empty set. The axioms are:

1) $b(\varnothing)=0$
2) For all the subsets A_i included in Θ

$$\sum_{A_i \subseteq \Theta} b(A_i) = 1 \tag{II.49}$$

3) For a collection of subset $\{A_1, A_2, \ldots, A_n\}$

$$b(A_1 \cup A_2 \cup \ldots \cup A_n) \geq \sum_{\substack{I \subset \{1, \ldots n\} \\ I \neq \varnothing}} (-1)^{|I|+1} \, b(\bigcap_{i \in I} A_i) \tag{II.50}$$

where $|I|$ stands for the cardinality of set I and the special summation is a sum over all sets I of indices which are subset of the set $\{1,2,\ldots n\}$.

An example of the third axiom is:

$$\begin{aligned} b(A_1 \cup A_2 \cup A_3) \geq {} & b(A_1) + b(A_2) + b(A_3) - b(A_1 \cap A_2) - \\ & b(A_1 \cap A_3) - b(A_2 \cap A_3) + b(A_1 \cap A_2 \cap A_3) \end{aligned} \tag{II.51}$$

An important consequence of the third axiom concerns the negation of a proposition

$$b(A) + b(\tilde{A}) \leq 1 \tag{II.52}$$

where the tilde over proposition stands for negation.

Suppose A_i and B_j are subsets of sets α and β, which are both subsets of the same frame of discernment Θ. If the belief associated to proposition A_i and B_j are independent, the belief of the combination or the intercept of both propositions is obtained from Dempster's rule of combination.

$$b(A_i \cap B_j) - \frac{b(A_i)\,b(B_j)}{1 - \sum_{r,s,A_r \cap B_s = \emptyset} b(A_r)\,b(B_s)} \qquad \text{(II.53)}$$

where the summation, over the indices r and s, is restricted to the subsets A_r and B_s so that the intercept between these subsets is equal to the empty set.

The fundamental particularity of the evidence theory is the computation of two parameters which gauge the likelihood of a proposition from the calculation of the belief of this proposition. The two parameters are a lower bound probability called the support and a upper bound probability called the plausibility. The support of any proposition A_i which belongs to the set Θ is the summation of the belief of all subsets of A_i and it is obtained from:

$$spt(A_i) - \sum_{r} b(A_{ir}) \qquad \text{(II.54)}$$

where the propositions A_{ir} are subsets of A_i. As an example of support calculation, if $A_i = A_{i1} \cup A_{i2}$ then

$$spt(A_i) - b(A_{i1}) + b(A_2) + b(A_{i1} \cup A_{i2}) \qquad \text{(II.55)}$$

The plausibility for this same proposition is given by

$$pls(A_i) - 1 - spt(\tilde{A}_i) \qquad \text{(II.56)}$$

where the negation of the proposition $\tilde{A}_i$ represents the union of all elements from Θ which have no intercept with A_i. From the above it can be demonstrated that the plausibility is equal to the summation of the belief of all subsets of Θ which contain at least a subset of A_i.

For the following application, the data contained in Table II.2 are used as sn MSDF attribute estimation database for inference. Evidential approach is less demanding in database requirements compared to a probabilistic approach since it does not require some a priori information about each possible target and for each sensor. In order to cover all the aspects of the approach, a fusion of the sensor attributes (proposition) reported at the same time and a fusion of the MSDF proposition reported at different times are performed below. Table II.8 shows some sensor propositions at two different times. At time 1, the MSDF function receives three sensor propositions and a belief value associated to each. The belief corresponds to the confidence level given in the other approach and it is usually calculated by the sensors. The frame of discernment is $\Theta = \{ A_1, A_2, A_3, A_4, A_5 \}$ and for each proposition the belief associated with this set is given. At the starting point the support of each proposition is equal to the belief value and the plausibility is one. The propositions which are indicated are not directly given by the sensors but are indirectly extracted by the MSDF attribute estimation process from the sensor declarations. For example the IFF has indicated that the target is friend with 90% level of confidence. Using the database information and the IFF declaration, the MSDF function built the proposition that the target under tracking is either target type A_4 or A_5.

Table II.8. Some Sensors Propositions at Two Different Times

Time	Sensor	Proposition	Belief	b(Θ)
1	IRST	A_4	0.7	0.3
	MRR	$A_1 \cup A_2$	0.8	0.2
	IFF	$A_4 \cup A_5$	0.9	0.1
2	IRST	A_4	0.7	0.3
	MRR	$A_1 \cup A_2 \cup A_4$	0.6	0.4
	ESM	$A_2 \cup A_5$	0.5	0.5

The first step will be to fuse the IRST and MRR propositions at time 1 using the equation (II.53). The two propositions are disjointed, therefore the summation in the denominator will have one term. For example the fusion between the belief in the IRST proposition and the belief in the frame of discernment from the MRR is given by:

$$b(A_4 \cap \Theta) = \frac{0.7*0.2}{1 - 0.7*0.8} = b(A_4) \qquad \text{(II.57)}$$

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The second step is the fusion of the IFF with the previously fused data. Table II.9 provides the results of these combinations. Also included are the results from the fusion of the three sensor propositions made at time 2. As seen in the last row, Dempster-Shafer's rule of combination sometimes leads to the creation of new propositions.

Table II.9. Fusion of Propositions for each Time Report

Time	Sensor	Proposition	Belief	b(Θ)
Time 1 Step 1	Fusion of IRST and MRR	A_4	0.318	0.136
		$A_1 \cup A_2$	0.545	
	IFF	$A_4 \cup A_5$	0.9	0.1
Time 1 Step 2	Fusion of IRST, MRR and IFF	A_4	0.624	0.0268
		$A_1 \cup A_2$	0.107	
		$A_4 \cup A_5$	0.241	
Time 2 Step 1	Fusion of IRST and MRR	A_4	0.70	0.12
		$A_1 \cup A_2 \cup A_4$	0.18	
	ESM	$A_2 \cup A_5$	0.5	0.5
Time 2 Step 2	Fusion of IRST, MRR and IFF	A_4	0.538	0.0923
		$A_1 \cup A_2 \cup A_4$	0.138	
		$A_2 \cup A_5$	0.0923	
		A_2	0.138	

Updated values of support and plausibility for each proposition can be computed after time 1 fusion. For example, using equations (II.54) and (II.56), proposition $A_4 \cup A_5$ has a support and a plausibility equal to

The statistical interpretation of these two numbers suggests that the detected target has a probability

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$$\begin{aligned} spt(A_4 \cup A_5) &= b(A_4) + b(A_4 \cup A_5) && = 0.856 \\ pls(A_4 \cup A_5) &= 1 - spt(A_1 \cup A_2 \cup A_3) && \\ &= 1 - b(A_1 \cup A_2) && = 0.893 \end{aligned} \qquad \text{(II.58)}$$

The statistical interpretation of these two numbers suggests that the detected target has a probability between 85.6% and 89.3% to be A_4 or to be A_5 or, in other words, to be any of the friendly targets in the database (Table II.2).

The fusion between the proposition at time 1 with those at time 2 can be performed according to the same methodology because it is reasonable to believe that the sensor data are statistically time independent of each other. Table II.10 shows the results, including the support and the plausibility. Another proposition A_3, for which no belief was available, becomes computable due to the knowledge inferred from the other propositions.

Table II.10. Attribute Fusion Results of Time 1 with Time 2

Proposition	Belief	Support	Plausibility
A_2	0.03718	0.03718	0.08083
A_4	0.86097	0.86097	0.89816
A_5	0.02910	0.02910	0.06467
$A_1 \cup A_2$	0.03233	0.06951	0.08083
$A_2 \cup A_5$	0.00323	0.06951	0.13903
$A_4 \cup A_5$	0.02910	0.91917	0.93049
$A_1 \cup A_2 \cup A_4$	0.00485	0.93533	0.97090
A_3	0.0	0.0	0.00323

The statistical interpretation of the results is extracted from the support and the plausibility. Alone the support or the plausibility represents the boundary where the real Bayesian probability of the proposition can be found. A good approximation of the Bayesian probability would be to say that it is equal to the middle point plus or minus half the width of the interval, i.e.,

$$\text{Bayesian prob.} = \frac{spt + pls}{2} \pm \frac{pls - spt}{2} \qquad (II.59)$$

The goal of the evidence theory is not to provide a support equal to one but support which as much as possible is equal to the plausibility. Instead of providing maximum certainty, evidence approach provides minimum ignorance about reality.

II.2.5.2.5 Fuzzy Logic

Fuzzy logic deals with approximate modes of reasoning [Zadeh, 1988]. In standard logic a proposition is either true or false. In fuzzy logic a proposition has a parameter value called "membership value" ranging from 0 (completely false) to 1 (completely true). Zadeh fuzzy logic is a well defined formalism which describes the fuzzy propositions and combination rules to create syllogisms and inferencing for using fuzzy probability.

Fuzzy logic application to the identity estimation problem is not documented in the literature as exhaustively as are the Bayesian or Dempster-Shafer approaches are. Actually, the Naval Ocean Systems Center, through the research performed by I.R. Goodman [Goodman, 1981 and 1985], is the only group active in this field. The value of fuzzy logic to data fusion is still being researched and more work remains to be done, especially comparison with other methods.

II.2.5.3 Association Using Both Kinematic and Attribute Data

Whatever data association technique selected, JPDA or Multiple Hypothesis Tracking (MHT), both use the classical probabilistic foundation. Therefore the attribute estimation process which uses the Bayesian approach discussed in section II.2.5.2.3 can be easily incorporated. The subject was first introduced by [Bowman and Morefield, 1980] and [Atkinson, 1980] and is discussed in [Blackman, 1986, ch. 13]. The incorporation changes the association decision criteria due to the introduction of new statistical variables, the attribute variables. The following example describes one possible implementation.

In a situation where an MRR report is to be associated with a particular six-dimensional MSDF track, the gating technique uses a chi-square distributed parameter which has 3 degrees of freedom and which gauges the correlation between the track and the report. The 95% and 99% thresholds in the case are 7.8 and 11.3. The two hypothesis (for the sake of simplicity the existence of other tracks are not considered) that are tested by the gate test are stated as follows:

H_0 = the report belongs to a new track
H_1 = the report belongs to this track

If the estimated attribute parameter of the track suggests a specific attribute with a very high probability, it should be easier to associate kinematically any report which declares the same attribute. This means that if the declared attribute of the report is unlikely compared to the estimated one of the track, the kinematic data of the report will have to be very close to those of the track. Using 99% for the threshold, the gate test without attribute, states

$$\begin{array}{lll} H_1 & \text{accepted if} & R^2 < 11.3 \\ H_0 & \text{accepted if} & R^2 \geq 11.3 \end{array} \qquad \text{(II.60)}$$

Where R is the statistical distance. It can be shown [Blackman, 1986, ch. 13] that the inclusion of the estimated attribute probability changes the decision criteria to

$$\begin{array}{ll} H_1 \text{ accepted if} & R^2 - 2\ln[P(B|\vec{\beta})] < 11.3 \\ H_0 \text{ accepted if} & R^2 - 2\ln[P(B|\vec{\beta})] \geq 11.3 \end{array} \qquad \text{(II.61)}$$

where B is the attribute variable which is suggested by the report and which must be estimated at the time of the report using the declaration history $\vec{\beta}$ of the track. As indicated an unlikely attribute measurement will often suggest the H_0 hypothesis and create new tracks.

If the evidential method is used, an equivalent number can be introduced to play the same role as $P(B|\vec{\beta})$ in relation (II.61). The subject is discussed in [Blackman, 1986] at the overview level. It is mentioned that the summation term in the denominator of the equation (II.53) is a measure of the disagreement between the beliefs of the propositions belonging to a track and the belief of the propositions belonging to a contact. It is suggested that this measure of disagreement can be the equivalent number. There is no formal result that supports this assertion and more studies are necessary.

II.2.5.4 Attribute Estimation and Fusion from Various Knowledge Sources

Attribute information from sources other than sensors must be entered in the MSDF function through the target assessment process, which in principle should have the appropriate management algorithms to sort and distribute the information in the other process. The data from the following knowledge sources: data links, intelligence, plan and command information, environmental data, equipment database, visual sightings, encyclopedic data and collateral types of information from sources ashore, are somewhat imprecise and subjective. If a level of confidence or some probability lower and upper bounds are provided with each type of information, the attribute estimation process that uses evidential method will be able to deal with this kind of information.

II.2.6 Application of AI Techniques

This discussion attempts to identify the current design and implementation issues along with the qualitative performance issues for the application of AI techniques to an MSDF function in the context of AAW. This will be done by analyzing the kernel processes and the input and output data requirements for different types of fusion algorithms in which AI techniques are being used. Wherever appropriate, the use of expert systems and neural networks as approaches for combining well understood theories and heuristic types of data is discussed. We adopt here the definition of Barr that "a heuristic is a rule of thumb that is not formally justified yet empirically yields good results" [Barr, Cohen and Feigenbaum, 1989].

There is abundant literature on the subject of application of AI methods and techniques to the multi-sensor data fusion problem both in military applications (target tracking, C^3I, etc.) and civilian applications (robotics, automatic translation, image processing, etc.). As some authors [Hall and Linn, 1991] warn, however, information about the increasing number of implementations of multi-sensor data fusion systems in the military sphere which reach the deployment stage is often restricted from being published in the open literature. This explains why publications discussing "inference based on negative information" were not found in the open literature. This in no way invalidates the discussion of general trends and issues pertaining to the subject.

In this report, the discussion of AI techniques will be structured around the products-oriented model developed by the Joint Directors of Laboratories/Data Fusion Subpanel (JDL/DFS) which describes the fusion process via the data processing results "levels". These three fusion products levels, as introduced earlier in section II.2, are:

- Level 1: the target state and identification (or "detection") (target tracking, data alignment, data correlation, identification) data;
- Level 2: the situation assessment data; and,
- Level 3: the threat assessment data.

Level 2 fusion concerns the construction of a generalized situational representation from incomplete sets of data to yield a contextual interpretations of the kinematic and attribute data of targets produced in Level 1. Level 2 fusion uses Level 1 fusion data and a technical and doctrinal database to yield indications and warnings about Level 1 targets. Level 3 fusion has to estimate the own force capability to engage the enemy efficiently and make propositions about appropriate responses. The inputs of Level 3 fusion are the Levels 1 and 2 data and a technical and doctrinal database.

Figure II.10 illustrates this conceptual model.

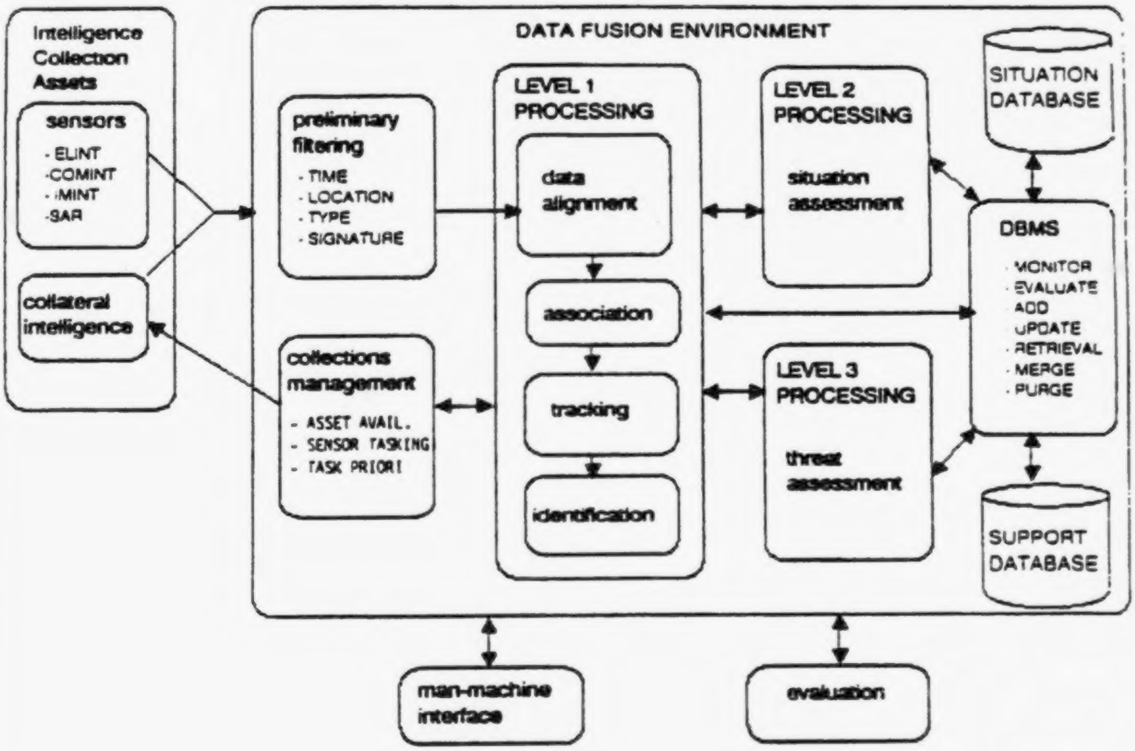
Intelligence Collection Assets
sensors
- ELINT
-COMINT
- IMINT
-SAR
collateral intelligence
DATA FUSION ENVIRONMENT
preliminary filtering
- TIME
- LOCATION
- TYPE
- SIGNATURE
collections management
- ASSET AVAIL.
- SENSOR TASKING
- TASK PRIORI
LEVEL 1 PROCESSING
data alignment
association
tracking
identification
LEVEL 2 PROCESSING
situation assessment
LEVEL 3 PROCESSING
threat assessment
SITUATION DATABASE
DBMS
- MONITOR
- EVALUATE
- ADD
- UPDATE
- RETRIEVAL
- MERGE
- PURGE
SUPPORT DATABASE
man-machine interface
evaluation

Figure II.10 JDL/DFS "products-oriented" Data Fusion model.

Most authors state that in general AI techniques are appropriate to applications involving Level 2 (hostile or friendly military situation assessments) and Level 3 (hostile force threat assessments) fusion processes, even though certain of its techniques find application to Level 1 (fused position and identity estimates) fusion operations. Thus, the role of AI in data fusion emerges mostly in applications requiring inference and reasoning, i.e., symbolic processing versus that involving measurement, i.e. numeric processing. In other words, it is desirable to combine more abstract data (i.e., "symbolic" rather than numeric data) based on the knowledge of relationships between data sets in order to gain more information about the sensed environment [Waltz and Llinas, 1990, ch. 12]. The data being processed is in the form of the symbolic representation of knowledge composed of facts, beliefs and heuristics.

In summary, the AI-data fusion relationship is a result of and is characterized by the ability to apply inferential and reasoning techniques via symbolic processing to data and knowledge involved in a data fusion problem. Thus, AI applications to data fusion processing, along with other application concepts and techniques, are most often applied to portions of Level 2 and Level 3 (from the JDL/DFS products-oriented model of the data fusion process) data fusion problems since these have the highest content of reasoning functions. AI techniques must be considered as part of a broad range of flexible solution strategies which provide the computational means of achieving reasoning power. This report addresses issues related to applications of AI to two of the Level 1 functions, target tracking and classification, and presents an overview of Levels 2 and 3 issues.

II.2.6.1 The General Applicability of AI Techniques

This section contains a discussion of the issues associated with the use of AI techniques and an analysis, for each type of AI technique used, of the kernel processes and their associated data requirements for algorithms used at the different levels of data fusion.

AI techniques are quickly emerging in data fusion applications. A recent survey done in the latter part of 1990 of the applications of data fusion [Hall and Linn, 1991] indicates that 24 of the 54 data fusion systems surveyed used AI methods and techniques. The majority of these were at the proof-of-concept or prototype stage but this may be a result of a bias in the survey following disclosure restrictions on deployed systems.

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II.2.6.1.1 Issues

Important issues pertaining to the applicability of AI techniques to data fusion are being investigated by the research community. Such issues include relevancy of the various AI techniques to each of the fusion levels, specification and design issues, uncertainty management and performance.

In a general sense, the relevancy issues can usually be solved by examining the inference ladder and selecting the appropriate AI technique. The inference ladder is a framework for comparing the level of inference with the level of data fusion and allows choosing, from the match, the "best" technique [Ball and Wold, 1988; Hall and Linn, 1990].

Design issues are those associated with the selection of system specification, design and development methodologies and tools [Haugh, 1988; Fox and Arkin, 1988; Waltz and Llinas, 1990, ch. 10], and integration of the AI techniques into the overall data fusion system architecture. AI techniques should be intrinsic to the design, of the MSDF system not an afterthought.

Uncertainty management in AI, underlining the limits of symbolic processing [Berenji, 1988], is another issue the MSDF system designer must contend with. Researchers have gradually realized that symbolic processing techniques are inadequate by themselves for establishing the degree of confidence associated with the inferences and decisions made when reasoning under uncertainty. The fact is now recognized that fuzzy logic, belief functions theory (or Dempster-Shafer evidence theory), and Bayesian probability theory techniques must be used in applications of AI.

The performance issues include computational requirements such as processing capacity of computer architectures [Adams, 1987; Bowman, 1988] database requirements and knowledge representation methods for achieving real-time processing [Antony, 1989B].

II.2.6.1.2 Analysis of AI Techniques

AI technology elements comprise techniques and applications. The techniques and applications of AI are listed in Table II.11 below. Techniques as referred to here are actually terms under which are grouped more specific techniques having their roots in symbolic processing.

[illegible]

Table II.11. AI Techniques and Applications

AI techniques	AI application
Inferencing	Automatic Programming
Knowledge Representation	Expert Systems (or KBS)
Pattern Matching	Intelligent Assistance
Search/Problem solving	Knowledge Acquisition
	Learning
	Machine Translation
	Machine Vision (Imaging)
	Natural Language Processing
	Planning
	Robotics
	Speech Understanding
	Text Understanding

It is claimed that the main applications of AI used in solving data fusion problems are: expert or knowledge-based systems, natural language processing (NLP), planning (i.e., plan recognition or management), learning and intelligent assistance (decision aid) [Waltz and Llinas, 1990]. In addition, some of the pattern matching techniques are used as types of solutions directly applied to data fusion problems.

The underlying techniques and methods subordinate to these applications and techniques may be partitioned in the following manner:

Knowledge-Based Systems:

Knowledge representation techniques

- scripts
- rules
- frames
- semantic nets
- analogical

Inference techniques/methods

- production rules

- blackboard
- action/object
- general problem solving

Search techniques

Uncertainty Management techniques

- Belief functions (D-S)
- Bayesian Probability
- Confidence Factor
- fuzzy set

Natural Language Processing:

Pattern recognition techniques

Knowledge representation techniques

- scripts

Planning:

Plan recognition techniques

- Schemata

Plan generation techniques

- procedural networks

Learning:

- artificial neural networks
- connectionist architecture

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Intelligent Assistance:

Knowledge Based Systems

Pattern Matching:

Pattern recognition

- event/object network templating
- Adaptive Neural Networks

These applications and techniques of AI are applied in specific contexts, i.e., Levels, of data fusion. As stated earlier, Level 1 fusion is not the area where most of the experiments in applicability of AI techniques have taken place. The main benefit of AI to Level 1 data fusion resides in the adaptability to the overall situation by applying expert reasoning in combination with the numerical methods (utility-based or scheduling theory-based approaches). At this level of data fusion, the primary techniques used are some type of pattern matching and the inference generation techniques, the searching techniques and others that are usually transparent within AI applications.

The most typical and numerous applications of AI to Data Fusion are found at Levels 2 and 3 since the JDL/DFS model reflects a hierarchy in degree of inferencing and reasoning culminating with Level 3. At these levels, by the very nature of the processes of situation assessment and threat assessment which involve numerous factors, parameters, and viewpoints not found at Level 1, a problem solving approach that can be translated into a processing approach is needed. Attempts to design and implement Knowledge-Based Systems (KBSs) for Command, Control, Communications and Intelligence (C^3I) have been made with increased magnitude since the early 80's [Brown, 1983; Houde, 1987]. Table II.12 below summarizes the applicability of AI techniques for each level of fusion.

Table II.12. Aplicability of AI Techniques to Levels of Fusion

AI Techniques	Level of Fusion		
	1	2	3
Knowledge-Based (Expert) Systems	X	X	X
Natural Language Processing		X	X
Planning		X	X
Learning		X	X
Searching		X	
Intelligent Assistance	X	X	X
Pattern Matching	X	X	X

This classification must not be considered as rigorous though, since the techniques often exceed the boundaries between the different levels of fusion and only indicate the major areas of applicability of the techniques.

It is also useful to determine where AI techniques and methods are applied within the MSDF function system architecture. Figure II.11 below illustrates a generic fusion system architecture where functions in which AI techniques form components are depicted as black boxes. Each of the functions and associated AI techniques will be presented in more detail in the following sections as the discussion will then focus on specific problems.

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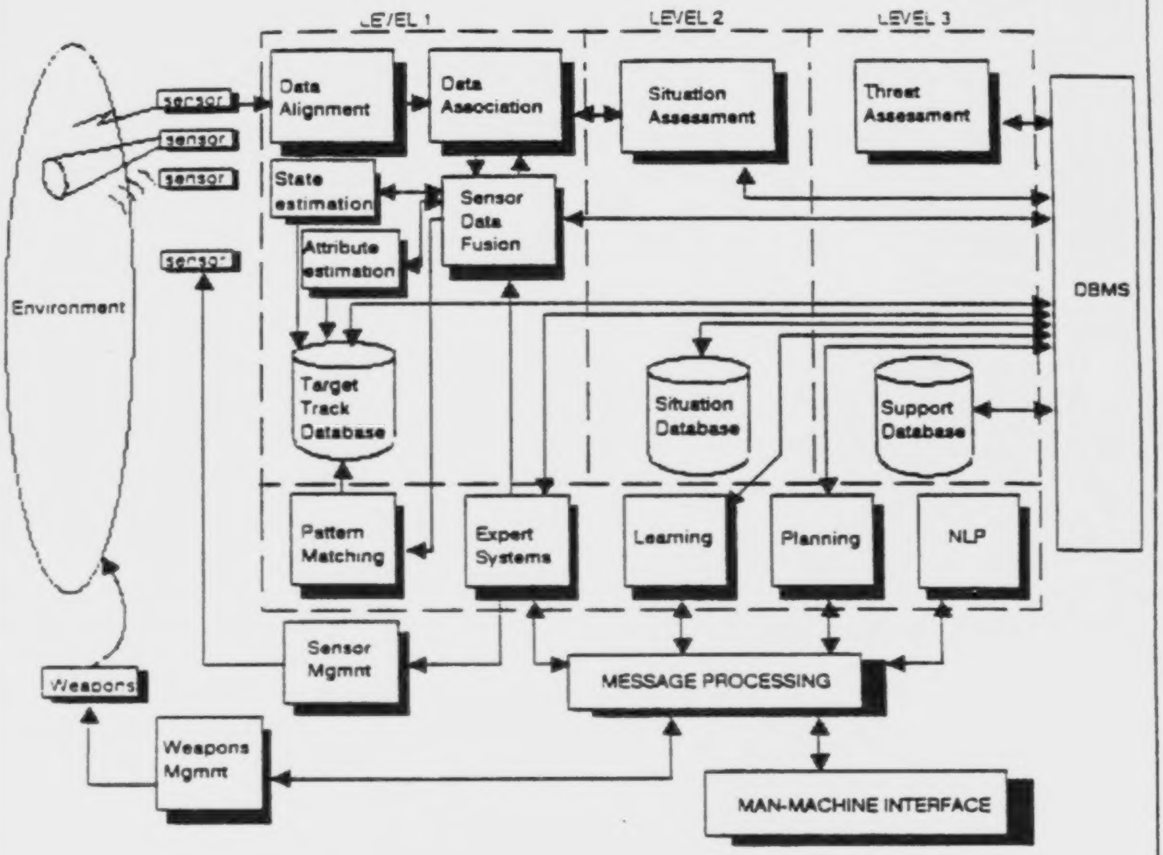
LEVEL 1
LEVEL 2
LEVEL 3
sensor
sensor
sensor
sensor
Environment
Data Alignment
Data Association
Situation Assessment
Threat Assessment
State estimation
Sensor Data Fusion
Attribute estimation
DBMS
Target Track Database
Situation Database
Support Database
Pattern Matching
Expert Systems
Learning
Planning
NLP
Sensor Mgmnt
Weapons
Weapons Mgmnt
MESSAGE PROCESSING
MAN-MACHINE INTERFACE

Figure II.11 Data Fusion System Architecture Model

II.2.6.1.3 Knowledge-Based Systems

As already indicated in Table II-10, KBSs also called Expert Systems (ESs), are used at all three levels of fusion. At Level 1, most fusion algorithms using KBSs, or ESs belong to the identity fusion category [Hall and Linn, 1990], with some very specific applications to positional fusion [Byrne, Miles, and Lakin, 1989; Waltz and Llinas, 1990 ch. 12] and to ancillary support functions [Hall and Linn, 1990]. The kernel process of a KBS is a computer program attempting to emulate some model of the human reasoning process. The input data generally consists of known data (facts) and new sensor report data that support inferences. The output consists of a declaration of inference.

For Levels 2 and 3, the main benefit resides in the capability to apply hierarchical inference strategies to solve combinatoric aspects of the problems (multi-level inferencing), and in the capability of applying decision and analysis support with cooperating KBSs to improve situation and threat estimating performance. These levels, corresponding to higher degrees of inference and of data abstraction, are where most of the applications of KBS to data fusion are found [Blackman and Broida, 1990; Waltz and Llinas, 1990].

At Level 2, use of KBS is dominant in the area of C^3I situation assessment [Ball and Wold, 1988]. The blackboard architecture method is frequently used to post hypotheses and results that are then shared by cooperating or non-cooperating expert systems to develop the tactical picture for situation assessment.

At level 3, KBSs are used in tactical applications of fusion, such as threat assessment [Lynch Carbone, 1990], and for strategic functions such as Ocean and Space surveillance.

II.2.6.1.4 Natural Language Processing

Aside from the Levels of fusion as such, the application of NLP to data fusion fulfils a generic function in the form of ancillary support algorithms. It controls three basic operations: message processing, advanced MMI, and data management support. *"NLP methods can be used as powerful fusion support tools for message-based systems, i.e., systems whose primary inputs are textual messages, to decipher or "read" such messages."* [Waltz and Llinas, 1990, p. 429] These functions are illustrated in Figure II-11.

II.2.6.1.5 Planning

There are some examples and discussions of this type of AI application in the literature surveyed [Benoit and Laskowski, 1990; Frankovich, Pedersen and Bernsteen, 1986]. Applications in this field use both pattern recognition techniques and plan generation techniques.

II.2.6.1.6 Learning

The techniques used in applications where learning is a prime function include rule-based systems as well as artificial neural nets, also referred to as connectionist models, parallel distributed processing models, or adaptive/self-organizing networks. There is a seeming overlap in techniques used for both learning and pattern recognition. This is because learning is often one of the initial steps in the process of pattern recognition where templating or other pattern matching methods are not used.

Experiments in sensor data fusion have produced promising preliminary results for the use of Adaptive Neural Networks (ANNs) [Ajjimarangsee and Huntsberger, 1988; Bowman, 1988]. An ANN is a computer which consists of a massively parallel interconnected network of simple units, or Processing Elements (PEs), intended to interact similarly to biological neural systems, and which has the capability to solve problems based upon sample data and built-in learning mechanisms. ANN capacity performance is continually improving and is dependent upon innovative Short Term Memory (STM), or "Content Addressable Memory", dynamics and Long Term Memory (LTM) training designs implementable in cost effective "analog" hardware.

II.2.6.1.7 Intelligent Assistance

Intelligent assistance is a set of techniques applicable to ancillary functions of the data fusion system. As the name implies, intelligent assistance centres around the establishment of a dialogue between a human operator and the data fusion system. This function is used in a few applications exemplified by the following list:

-Man-Machine Interface (MMI): - decision aid
- Indication & Warning
- alerting.

The implementation of intelligent assistance is usually via a KBS and Planning techniques [Benoit and Laskowski, 1990].

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II.2.6.1.8 Pattern Matching

The term of Pattern Matching regroups a number of AI techniques. Most of these are an instantiation of a form of template. Logical templates is one such instance of pattern matching techniques being used for data fusion.

Neural networks is another instance of a specialized form of template [Antony, 1989a] being used in a constantly increasing way for several applications at each of the three levels of data fusion. The foremost domain of application of this technique is in pattern recognition for identity fusion (Level 1) where multiple sensor data is transformed into a joint declaration of identity for a particular target [Waltz and Llinas, 1990,ch. 7, p. 228]. Many attempts in the past have been made and are still being pursued today to implement an effective Automatic Target Recognition (ATR) system. Also, the possibility of using neural nets at Level 1 fusion for multiple target tracking has been examined [Kuczewski, 1987] based on the computational benefits it offers over traditional algorithmic approaches, since with the neural net approach the computation time is completely independent of the number of tracks. Section II.2.6.2.3 below discusses in more detail the application of AI techniques to identity fusion.

II.2.6.2 The Applicability of AI Techniques to Target Tracking and Classification

This section contains an analysis of the applicability of AI techniques to specific problems of Level 1 data fusion, mainly target tracking and classification applications. The analysis will once again focus on the kernel processes and their associated Level 1 data fusion algorithm data requirements.

From the literature surveyed it appears that at the level of the data fusion subject of this report, the main areas of application for AI techniques are those of the selection of optimal algorithms, sensor management, and pattern recognition for target identification and classification.

As previously noted, it appears that most of the open literature surveyed discusses general issues related to the implementation of AI techniques on demonstration or research prototypes only. Little is disclosed, for evident security reasons, about the implementations on deployed fusion systems.

II.2.6.2.1 Real-Time Selection of the Best Correlation/Tracking Algorithm

The most potent AI technology currently available for achieving real-time selection of correlation/tracking algorithms is that of the KBSs. There are some discussions in the literature surveyed [Reiner, 1985; Waltz and Llinas, 1990] about the use of KBSs as algorithm selectors to deal with the tracking of highly manoeuvrable targets and making inferences about the next manoeuvre, at Level 1. However, there is no evidence as yet of implementation of such a method in an actual system.

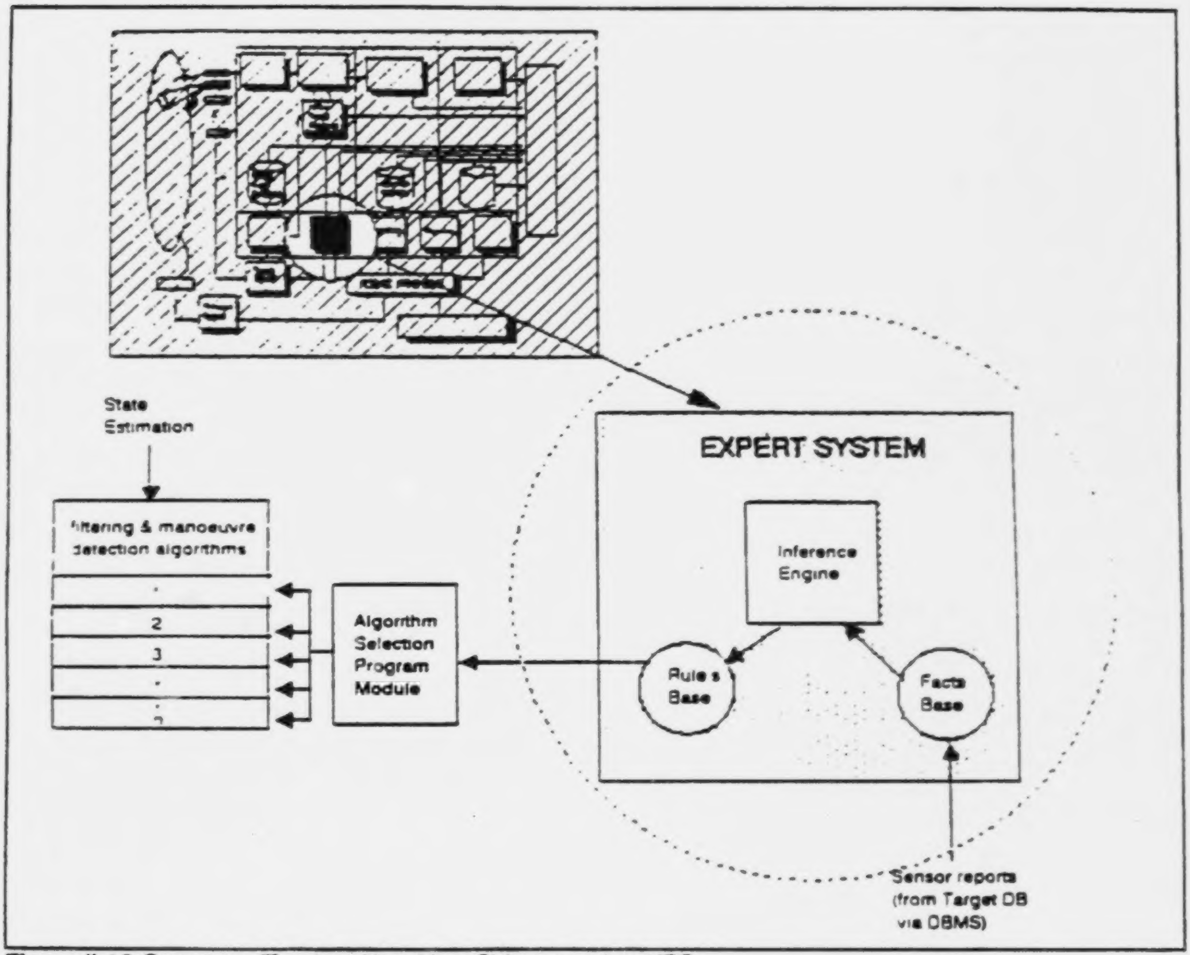
State
Estimation
filtering & manoeuvre
detection algorithms
1
2
3
.
n
Algorithm
Selection
Program
Module
EXPERT SYSTEM
Inference
Engine
Rules
Base
Facts
Base
Sensor reports
(from Target DB
via DBMS)

Figure II.12 Correlator/Tracker Algorithm Selector using KBS

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Conceptually, the idea is that there exists an optimal algorithm for performing the association and estimation processes. Figure II.12 illustrates the concept of an algorithm selector. By applying contextual knowledge and knowledge of algorithm performance the KBS selects and invokes the "best" algorithm available, from an inventory database of tracker algorithms, for the estimated current problem.

With the three standard tracker-correlator functional architectures, i.e., centralized, autonomous, and hybrid, difficulties arise from the fact that, first, in some cases it might not be possible to anticipate what precise problem the system may encounter and, second, from the fact that military tracking problems significantly change over time because of evolving threat characteristics. The KBS-based algorithm selector approach alleviates these difficulties by dynamically monitoring the tracker algorithm performance in the changing environment.

While solving some of the difficulties attributable to limitations of standard tracker-correlator architectures, the KBS algorithm selector approach raises some of its own. Namely, computational requirements increase by order of magnitude when symbolic processing is brought into play.

II.2.6.2.2 Manoeuvre Detection

Perhaps the greatest challenge in multisensor data fusion resides in the assigning of the association of heterogeneous sensor data in time and space to individual target files. This difficulty is compounded by increasingly stealthier high speed manoeuvring threats.

Solutions discussed in the literature for the manoeuvre detection problem have been proposed using numerical methods only. The possibility and trade-off studies of using numerical methods alone, a combination of numerical and symbolic methods, and symbolic methods alone have not been examined yet. Section II.2.8 of this report provides a discussion of numerical methods.

A possible application of an intelligent system to the problem of manoeuvre detection would be in the case where the electromagnetic energy density information supplied by the sensor could be used directly by a KBS to infer a manoeuvre more quickly than would the parametric-based filtering functions. For example, a jet aircraft target being tracked from an AAW platform by a medium range radar sensor presents a certain "aspect" or Radar Cross Section (RCS) that forms its signature. A human operator will immediately see upon a target manoeuvre a sudden change in energy density spectral information as a result of the change in aspect of the target cross-section to the sensor. At the same time, it will take the parametric detection filters a few scans before they resolve that a manoeuvre is occurring. The statistically based target manoeuvre algorithms require more time to detect the manoeuvre because it is dependent on the positional information update rate of the sensor system. Therefore, KBS given that constraints of computational capacity is not a limiting factor, could theoretically be used to emulate the human operator function and achieve target manoeuvre detection. PARAMAX recognizes here a potential further research topic worthy of investigation.

An example of using a combination of numerical and symbolic methods to achieve target manoeuvre detection can be found in [Eggers and Khuon, 1989]. This experiment demonstrated that a combination of statistically based adaptive preprocessing (signal processing) and neural networks could be successfully used to achieve detection of object manoeuvres simultaneously observed by two radars of different aspect, frequency and resolution.

II.2.6.2.3 Pattern Recognition (Target Identification and Classification)

To successfully achieve target classification and identification, an attribute fusion (or identity fusion) function is required which will combine all the sensor data associated with each target in the situation database to identify the target by assigning it to a class on the basis of common attributes. These attributes may belong to a set of direct sensor measurement features, behavioral characteristics, or contextual information. Table II.13 summarizes specific attributes for each of these categories.

Table II.13. Target Attributes for Identification and Classification

Direct measurement attributes	radar signature IR signature acoustic signature kinematic envelopes
Behavioral characteristics	aircraft velocity altitude flight envelopes target formations
Contextual information	logical relationships (IF-THEN or Boolean) intelligence data

The combination-inference function processes use these attributes and other information as a priori knowledge. These processes include structural models, behaviour models, heuristic inference rules and numerical classification algorithms [Waltz, Llinas, 1990]. For each of these processes a set of different methods and techniques, whether conventional algorithms, structured algorithms, or symbolic

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reasoning, are used. A generally agreed upon taxonomy of identity fusion algorithms at Level 1 [Hall and Linn, 1989, p. 606; Waltz and Llinas, 1990, p. 215] has been developed in which the different methods and techniques have been grouped under three broad categories: (1) physical models, (2) parametric classification, and (3) cognitive-based models.

The physical models category includes simulation and estimation methods to estimate identity, but are not being used in most operational fusion systems. Parametric classification includes both statistical based, such as classical inference, Bayesian, and Dempster-Shafer methods, and information theoretic techniques including AI techniques such as adaptive neural networks. The category of cognitive-based models is where most of the AI techniques find application. These techniques include logical templating and KBSs (expert systems and fuzzy set theory).

For structural models where the relationships between measured target attributes and target or target class are defined, the AI technique of Frames is commonly used since these relationships are typically of a hierarchical connection nature (IS-A and IS-A-PART-OF).

In the case of behavioral models the data may consist of both doctrinal knowledge (calling upon a knowledge base) and of newly acquired knowledge (acquired through the use of neural nets).

Heuristic inference rules, using production rules such as simple IF-THEN and AND, OR, or COMPLEMENT Boolean relationships, form the basis for constructing logical templates. The logical "templating" technique has been successfully used since the mid-70s for pattern recognition. Early system implementations using this technique were based on FORTRAN programs and relational data models, but recent systems are using expert systems. Some authors [Hall and Linn, 1989] have commented on the conceptual description of this technique and given examples of implementation.

Numerical classification algorithms are used to quantify the confidence level of the membership of combined target attributes to the target classes. Fuzzy set theory and other mathematical techniques are now starting to be used to complement symbolic processing techniques in performing uncertainty management [Berenji, 1988].

II.2.6.2.4 Inference of the Existence of Likely But Undetected Target Threats

Target tracking is normally achieved through the association of sensor measurements or reports with previous observations (contact-to-track) or with parallel observations (contact-to-contact). If a static target (e.g., hovering jet or helicopter) is detected or a dynamic target is intermittently detected (as in the case of adverse atmospheric conditions) then it is necessary to use a process referred to as target localization. Target localization is achieved by the association of multiple lines of bearing to derive

[illegible]

a region of space within which a target exists with a specified probability.

Multisensor Data Fusion system designers must also deal with information security considerations to counter the selective jamming of sensors in a multisensor suite which may create blind spots in the coverage domains, thereby creating an opportunity for undetected targets or activities.

The solution to this problem lies with the design of intelligent systems that will combine the heuristics of experts with methods for achieving a high degree of confidence with the data being processed.

The generalized data fusion process model developed by Antony [Antony, 1989A] elaborates on the 'situation abstraction' processes of situation generalization and situation specialization. These processes aim at inferring the existence of entities or events based on fragmentary information.

II.2.6.2.5 Inference of the Expected Number of Targets

The techniques used in making inferences about the expected number of targets are mostly those of KBS as doctrinal knowledge comes into play after positive identification of the hostile platform. The assessment of the a priori probability used in the Bayesian approach for attribute estimation would benefit from the use of the KBS technique. As already mentioned in section II.2.5.2.3, the Bayesian approach requires an initial a priori probability in order to start the attribute estimation process. Without any clue about the expected number of targets, the approach uses the maximum likelihood value **1/s** where **s** is the number of target classes. With the possibility to infer from a KBS the expected number of targets in a specific area, the Bayesian approach will converge more rapidly to the attribute probability.

II.2.6.2.6 Inference of the Expected Future Heading

At Fusion Level 1, tracking is one of the prime processes. While conventional numerical approaches attempt to predict the next position based on laws of physics they have limited capabilities in predicting behaviour. Heuristic knowledge about tactical patterns for each target class is required in order to infer about future events, such as manoeuvres. Manoeuvre detection has already been discussed in section II.2.6.2.2, above. Prediction of the new heading immediately following the manoeuvre may be used to maintain tracking or reacquire the track if it had been lost.

Little effort has been spent thus far in developing and testing AI-assisted tracking systems. One of the authors in our survey reported on this type of application [Vannicola and Mineo, 1988]. The conceptual basis for this type of application is that large a priori databases (domain knowledge) and large a posteori databases (learned knowledge) can be used with an inference engine dedicated to performing the knowledge based signal, data and track processing. By limiting the possible trajectories based on known constraints of target dynamics, a higher false alarm rate is allowed by lowering the detection threshold. A template is created if the threshold crossings do not associate with known target dynamics or previous scan information. Research is continuing as initial results demonstrate superior performance in high target densities and high clutter situations. Another approach, called "Multispectral Multisensor Fusion Program" [Vannicola and Mineo, 1988], accounts for uncertain time and place of target appearance, target manoeuvres to evade surveillance, measurement inaccuracies, combined data from multiple sensors, different coverage areas, and target aspect geometries. Using a suite of sensors covering a wide spectral scale, this approach applies gating and decision making to optimally predict, update, and prune tracks again based on the target dynamics and on the sensor location and measurement model parameters.

II.2.6.2.7 Advanced Sensor Management Concepts

Sensor management in a multiple sensor data fusion system is highly desirable for optimizing the collective performance of sensors. The main categories of sensor management are spatial management, mode management, and temporal management. The operational requirements criteria justifying sensor management include detection and tracking performance monitoring, search coverage and rate, emissions control, continuity of coverage over time, and target identification.

Six basic functions are generally recognized in sensor management. These include target ranking, event prediction, sensor prediction, target-sensor assignment, spatial and temporal coverage control, and allocation and control strategy [Waltz and Llinas, 1990]. Other authors use slightly different functional structure and terminology [Bier, Rothman and Manske, 1988] but also advocate the use of AI techniques for sensor management systems. The target ranking function is required to determine the relative priority of detected targets in order to assign sensor resources accordingly. The event detection function responds to the need for predicting future events and to manage sensors to detect or verify anticipated events. Sensor prediction as a function is used to establish the ability (availability or capability) of sensors using Boolean matrix methods or sensor performance models to quantify the value of each sensor-target pairing for future sensor assignments. The target-sensor assignment function is based on the optimization of a composite objective function of both target priorities and sensor-target performance values. Directional sensors must be managed from the aspects of both the spatial volume coverage and the amount of time spent searching in each spatial volume and is accomplished by the spatial and temporal coverage control function. Finally, the allocation and control strategy function ensures the conversion of assignment solutions into commands to sensors with some additional control factors: counter-countermeasure, EMCON, cuing and hand-off, and scheduling of sensor controls. The AI technique most often cited for applications where Level 1 fusion is

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implemented as a feedback control process is that of the KBS since it provides a means for applying expert knowledge for sensor control and employment strategies [Waltz and Llinas, 1990, p. 429].

One of the proposed methods for implementation [Blackman and Broida, 1990] of expert systems to sensor allocation suggests that the algorithm would consist of first determinate, from target kinematic estimates and quantitative knowledge about the target (i.e., distance, closing rate, bearing). Then, qualitative knowledge, e.g., target type estimate, is defined and the fuzzy set membership to quantitative knowledge sets of each target, such as membership to the set "close" based on the computation of the range/range-rate, is determined. In the following step the membership in the qualitative knowledge fuzzy sets, defined by qualitative concepts such as "dangerous", of each target is computed using IF-THEN rules. Another set of rules is used to finally define the desirability of track update and the update priorities of tracks before the sensor allocation is performed.

II.2.6.3 Performance Analysis of AI Techniques

In this section the performance issues associated with the implementation of AI techniques will be analyzed both from an overall system perspective and from the point of view of individual techniques.

Again, the issues discussed earlier of selecting the optimal AI techniques and of achieving a truly integrated design of both the sensor suite and the other fusion processing elements must be considered from the start to attain superior performance objectives.

II.2.6.3.1 Performance Requirements

Response times of less than .2 seconds have been cited as a minimum requirement for effective intelligent data fusion systems [Kandyba, 1990]. This requirement should dictate the necessary update rates for sensors to acquire and track targets. For this to occur, system integrators should change their approach from reactively attempting to match existing sensor subsystems via the accommodating design of the C^2 system to preemptively specifying the requirements to the vendors.

Hardware and software providing greater computational power is required. The information output from the system should be in a highly cognitive form for the users.

II.2.6.3.2 Overall System Performance

Until recently, multiple sensor data fusion systems were designed by integrating existing sensors which themselves were not optimally designed for a data fusion architecture. The next generation of sensors should be designed with the requirements of data fusion in mind. The research effort in the field of intelligent data fusion is continually increasing and the main thrust seems to be towards a more integrated fusion system employing distributed sensor architectures and AI techniques in conjunction with conventional statistical methods to achieve higher resolution and better performance.

Advances in both hardware and software have made the implementation of practical AI-based systems increasingly feasible. Semiconductor manufacturers are now developing new integrated circuits which specifically fulfil the requirements of symbolic processing. These chips offer a totally reconfigurable architecture that allows the neural networks to be trained within the IC. Intel has developed neural circuit chips such as their 80170NW which is a CHMOS III EEPROM that integrates 64 PEs (quasi-similar to biological neurons) and a maximum of 10,240 analog weights (equivalent to synapses) [Schwartz, 1990]. The PEs are fully interconnected within the 80170 with a design that allows for the weights from the input, middle, and output layers to be simultaneously loaded into the 10,240 weight matrix. This design permits the multiplexing of the PEs so that a backpropagation network with a single hidden layer can be executed by a single chip at two billion Interconnections Per Second (IPS). While this is still far from the human brain's capabilities (up to 150,000 synapses per neuron) it makes possible the type of symbolic processing required to achieve reasonable performance. The difference between digital integrated circuits and neural circuits lies in the fact that, contrary to the former, input and output is not a digital "on or off" state but instead a wide voltage range that provides from five to eight bits of resolution. Other manufacturers are developing similar chips using different approaches and strategies. It is expected that by the end of the decade practical real-time systems will integrate this technology.

For more conventional data processing and KBS, more compact massively parallel scalable-architecture supercomputers are being produced such as the Associative Processor (AP) computers. Use of APs in multiobject tracking problems, mostly radar tracking, has been found quite useful for a long time [Allen, Kurien and Washburn, 1986]. During the last decade, intensive research and development leading to very dense integrated circuits and of massively parallel architecture computers [Adams, 1987] has made available a sufficient level of processing power to cope with the heavy computational requirements of symbolic processing solutions for the data fusion problem.

Selection of the most appropriate AI technique for the problem at hand is another issue influential for system performance. Previous experiments in intelligence fusion [Ball and Wold, 1988] have shown that techniques should not be used for the sake of technology.

KBSs

As one of the authors noted [Kandyba, 1990; Waltz and Llinas, 1990 p. 427], the development of real-time KBSs is faced with the problem of not having a unique procedural resolution path by the very nature of the inferencing process. This makes system performance difficult to predict.

Neural Networks

A number of experiments have been performed using neural networks, especially for fusion of identity data. Since the theoretical framework remains to be stabilized, basic issues are still to be understood before performance analysis can start.

II.2.7 Target State Estimation Analysis

II.2.7.1 Introduction

State estimation is a statistical process used to evaluate the state of a static or dynamic target based on collected measurements. The state refers to the position, velocity and acceleration of an object in space. The state estimate of an object is normally implemented with linear statistical estimators [Waltz and Llinas, 1990, ch. 6]. In this section some basic linear estimators are examined in order to see practical methods by which to implement them.

In tracking processes there are two general methods for processing the information given by sensors to estimate the state of the target. These are the batch and the recursive methods.

Given a set of scans collected by a sensor, the batch method processes all the measurements together to form target tracks and state estimates. The batch processing techniques are usually utilized for static locations problems. Batch processing demands high computational capabilities since it requires the storage and process of a lot of information at once as more and more data are received. Batch processing is viewed as an optimal solution for estimation problems but simplification of this method using recursive technique can be made for real-time implementation. [Blackman, 1986, ch. 1; Waltz and Llinas, 1990, ch. 6].

The recursive methods are generally utilized for dynamic targets. They process the measured information received from the sensor at each scan using only data received on that scan to update the results of previous processing [Blackman, 1986, ch. 1; Waltz and Llinas, 1990, ch. 6].

The following study of target state estimation proposes a general definition of state estimation so as to proceed further with the most utilized filtering techniques. The weighted least squares estimator and the maximum likelihood estimator which are batch processors will be discussed first. Then recursive processing filters such as the recursive form of the least squares estimator and the Kalman filter will follow. Some variations of the Kalman filter including the Upper Diagonal (UD) factorization form for the Kalman filter will also be examined.

Other types of filters will then be discussed: the α-β and α-β-γ and the modified polar coordinate filters. The equations given for all types of filters and techniques studied in this chapter are not derived in the text. In most cases they are given with logical explanations and the appropriate references so that one can refer to the source. This chapter can be used as a reference section for other chapters of this document where state estimation is mentioned.

II.2.7.2 State Estimation

For tracking problems, the state estimation process is necessary to estimate the position and velocity of the target as precisely as possible, given measured observation data from sensors. The model observation equation that relates the observed quantities $\vec{Y}$ of the target true state vector $\vec{X}$ is given as [Waltz and Llinas, 1990, ch. 6; Blackman, 1986, ch. 2]

$$\vec{Y}(k) = H(k)\vec{X}(k) + \vec{V}(k) \qquad \text{(II.62)}$$

where H(k) is the measurement matrix and $\vec{V}(k)$ is the measurement noise with white zero mean sequence with covariance R_k.

Thus, given a redundant data set $\vec{Y}$, the estimation problem tries to determine the value of $\vec{X}$ that best fits the observational data. Estimation techniques are usually utilized to determine the state vector $\vec{X}$ given the vector $\vec{Y}$. Linear statistical estimators would be the solution for physical implementation and for optimal state estimation of the target. The basic statistical estimators suggested here are the weighted least squares, the maximum likelihood and the minimum variance estimators. These estimators are made linear under the assumption that model equation can be made linear.

Figure II.13 shows an example of a basic state estimation model that can be used for static and dynamic applications [Waltz and Llinas, 1990, ch. 6]. The measurement process box flows from the observation model equation (II.62). The linear estimator box will use one of the estimation techniques proposed. Then, the error calculation box allows the calculation of the residual required for estimation techniques. The residual equation is given as [Bar-Shalom and Fortmann, 1988, ch. 2]

$$\vec{Z}(k) = \vec{Y}(k) - H(k)\hat{X}(k) \qquad \text{(II.63)}$$

where $\vec{Z}$ is the residual and $\hat{X}$ is the estimate of $\vec{X}$ at time k. In the sections II.2.7 and II.2.8, all vectors representing an estimated state are explicitly differentiated from other vectors by the hat symbol instead of an arrow.

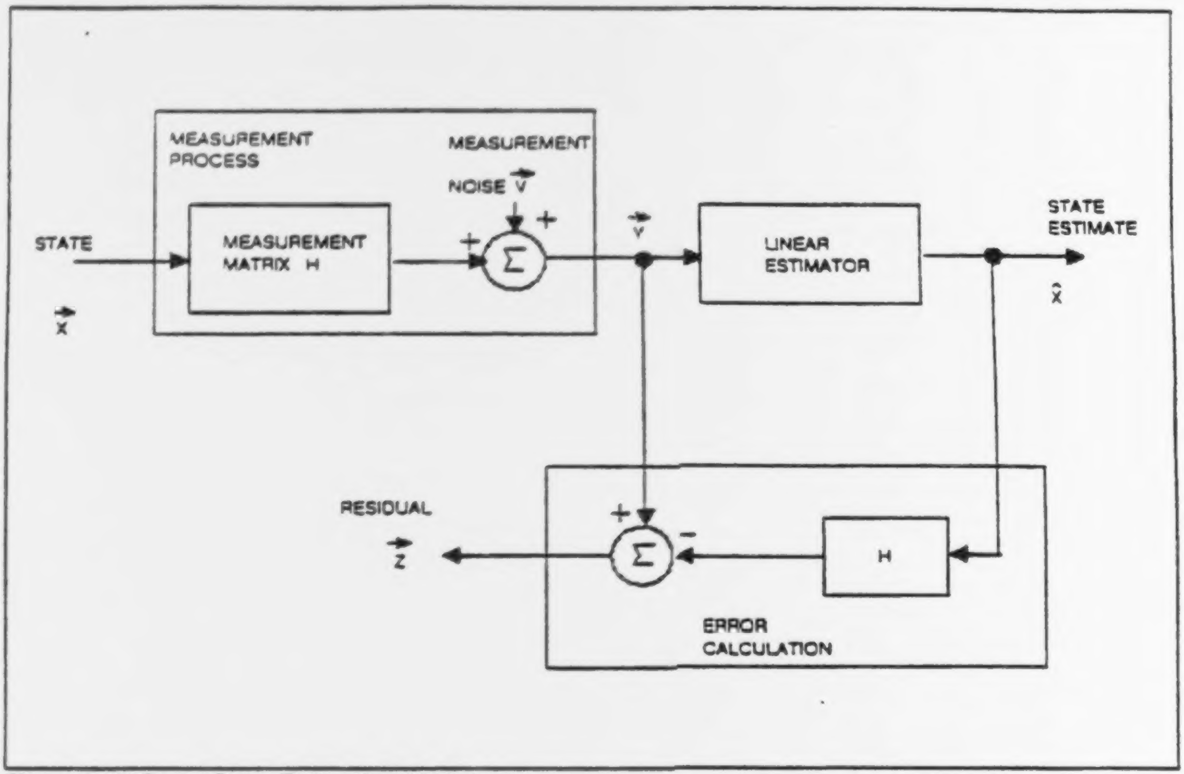
MEASUREMENT PROCESS
MEASUREMENT NOISE $\vec{v}$
STATE
$\vec{x}$
MEASUREMENT MATRIX H
+
+
Σ
$\vec{y}$
LINEAR ESTIMATOR
STATE ESTIMATE
$\hat{x}$
RESIDUAL
$\vec{z}$
+
-
Σ
H
ERROR CALCULATION

Figure II.13 Basic State Estimation Model

II.2.7.3 Filtering Techniques

In this section the batch and recursive techniques for processing sensor data for target state estimation are described. The recursive estimator examined later is the well known Kalman filter which seems to be the most often used by scientists since it provides optimal state estimates. Other forms of Kalman filtering techniques will also be discussed. Before going further with the recursive techniques, the basic batch processing filters are discussed below.

II.2.7.3.1 Batch Processing Filters

In this subsection two types of batch processing estimators applied for the static case (i.e., time-invariant) where the estimator is a linear function of the measured values are described. The basic linear statistical estimators discussed are the weighted least squares and the maximum likelihood estimators.

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II.2.7.3.1.1 Weighted Least Squares Estimator

The least squares method is a common estimation procedure for non-Bayesian parameters. From the measurement sequence of equation (II.63), the problem is to estimate the unknown constant vector $\vec{X}$ so that the resulting estimate $\hat{\vec{X}}(k)$ minimizes the quadratic error [Bar-Shalom and Fortmann, 1988, ch. 2]

$$\vec{J}(k) = \sum_{i=1}^{k} [\vec{Y}(i) - H(i)\vec{X}]^{T}[R]^{-1}(i)\,[\vec{Y}(i) - H(i)\vec{X}] \qquad \text{(II.64)}$$

where T denotes the transpose. This is rewritten as

$$\vec{J}(k) = [\vec{Y}^{k} - H^{k}\vec{X}]^{T}[R^{k}]^{-1}[\vec{Y}^{k} - H^{k}\vec{X}] \qquad \text{(II.65)}$$

for simplicity, where

$$\vec{Y} = [\vec{Y}(1), \ldots, \vec{Y}(1)]^{T} = \vec{H}^{k}\vec{X} + \vec{V}^{k}$$

is the staked vector of measurements.

$$\vec{H}^{k} = [\vec{H}(1), \ldots, \vec{H}(k)]^{T}$$

is the staked measurement matrix,

$$\vec{V}^{k} = [\vec{V}(1), \ldots, \vec{V}(1)]^{T}$$

is the staked vector of the measurement error (noise) and

$$\vec{R}^{k} = \text{diag}\,[\vec{R}(1), \ldots, \vec{R}(k)]$$

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is a block-diagonal, positive definite matrix. The weighting matrix R^k is the noise covariance which allows the estimator to reduce the square of certain error components. This would make a greater contribution to the solution in terms of accuracy [Waltz and Llinas, 1990, ch. 6].

The least squares estimate that minimizes $\vec{J}(k)$ is obtained by setting its gradient with respect to $\hat{X}(k)$, to zero, which yields [Bar-Shalom and Fortmann, 1988, ch. 2; Hassab, 1990, ch. 16]

$$\hat{\boldsymbol{X}}(k) = [(H^k)^T(R^k)^{-1}H^k]^{-1}(H^k)^T(R^k)^{-1}\vec{\boldsymbol{Y}}^k \qquad \text{(II.66)}$$

Therefore, the resulting minimal value $\vec{J}$ of the quadratic error, which is the weighted sum of the squares of the residuals, is the best fit for the estimated state.

With the assumption that $\vec{V}(i)$ are independent with zero mean random variables with covariances $\vec{R}(i)$, the mean square error covariance of the estimate is given as [Bar-Shalom and Fortmann, 1988, ch. 2; Hassab, 1990, ch. 16].

$$P = E[(\vec{\boldsymbol{X}} - \hat{\boldsymbol{X}}(k))(\vec{\boldsymbol{X}} - \hat{\boldsymbol{X}}(k))^T] = [(H^k)^T(R^k)^{-1}H^k]^{-1} \qquad \text{(II.67)}$$

II.2.7.3.1.2 Maximum Likelihood Estimator

The maximum likelihood estimator is another type of batch estimator that can be used to get the optimal solution for target position. It maximizes the likelihood function that characterizes the probability of any value of the target state vector conditioned on the observed measurements. The likelihood function is the joint probability distribution between the possible values of the random variable and the actual value observed [Waltz and Llinas, 1990, ch. 6]. This function can have practical uses for filtering applications. It can be used for detection and to check the consistency of a filter. The likelihood and the modify log-likelihood functions can also be used to test the goodness of fit of measurements to different noise models or to different tracks in a clutter environment, and to compare two or more candidate tracks [Bar-Shalom and Fortmann, 1988, ch. 2]. Mathematically the likelihood function is given as [Hogg and Tanis, 1983, ch. 5]

$$\Lambda(\vec{X}) = \prod_{i=1}^{k} p(\vec{Y}^{i} \mid \vec{X}) \qquad \text{(II.68)}$$

where $\vec{Y}$ is the measurement sequence.

The state vector that maximizes $\Lambda(\vec{X})$ is called the maximum likelihood estimator and is denoted as $\hat{\vec{X}}^{ML}$. The maximization of this function can be achieved by taking the partial derivative of the likelihood function of equation (II.68) with respect to the parameters to be estimated and equating it to zero. In some applications, non-linear estimations are used for optimal target position solution because of some geometric functions in the location equations. These geometric equations can be made linear based upon a maximum likelihood estimator [Waltz and Llinas, 1990, ch. 6].

The best way to illustrate the principle of the maximum likelihood estimator is to give a particular example where the state $\vec{X}$ and the variance σ^2 are to be estimated assuming that k measurements are made;

$$\vec{Y}(j) = \vec{X}_K + \vec{V}(j), \qquad j = 1, 2, \ldots k \qquad \text{(II.69)}$$

and $\vec{V}(j)$ are Gaussian, zero mean noise with variance σ^2. The likelihood function of equation (II.62) for the Gaussian probability density function (pdf) is

$$\Lambda(X) = \frac{1}{2\pi^{k/2}\sigma^{k}} \cdot \exp\left[-\frac{1}{2\sigma^2}\sum_{i=1}^{k}[\vec{Y}(i) - \vec{X}]^2\right] \qquad \text{(II.70)}$$

The above sum in the exponential results from the product of the exponents.

The maximum likelihood is found by setting the derivatives of the natural logarithm of the likelihood function to zero with respect to $\vec{X}$ and σ. Therefore the mean estimator $\hat{X}$ is given as

$$\hat{\vec{X}}^{ML}(k) = \frac{1}{k}\sum_{i=1}^{k}\vec{Y}(i) \tag{II.71}$$

and the estimate of the simple variance is given as

$$[\hat{\sigma}^{ML}(k)]^2 = \frac{1}{k}\sum_{i=1}^{k}[\vec{Y}(i) - \hat{\vec{X}}^{ML}]^2 \tag{II.72}$$

The maximum likelihood of the mean $\hat{X}$ and the variance $\hat{\sigma}^2$ of the Gaussian distribution are the corresponding characteristics of the sample measured. Further discussions and examples on the maximum likelihood theory are given in [Hogg and Tanis, 1983, ch. 5 ; Bar-Shalom and Fortmann, 1988, ch. 2].

II.2.7.3.2 Recursive Processing Filters

In this subsection we present the weighted least squares estimator applied for the static case that can be made recursive. The concept of linear estimation technique discussed above is extended to the case of dynamic quantities. The Kalman Filter equations and the Kalman Filter algorithm are given. Finally, the α-ß and the α-ß-γ filters are discussed.

II.2.7.3.2.1 Recursive Form of Least Squares Estimator

A batch or the least squares estimator can be expressed in a recursive form. The new state equation for the batch estimation given in equation (II.66) for (k+1) in a recursive form is given as [Bar-Shalom and Fortmann, 1988, ch. 2]

$$\hat{\mathbf{X}}(k+1) = \hat{\mathbf{X}}(k) + K(k+1)[\vec{\mathbf{Y}}(k+1) - H(k+1)\hat{\mathbf{X}}(k)] \tag{II.73}$$

where the gain K(k+1) and the measurement covariance S(k+1) are defined as

$$K(k+1) = P(k)H^T(k+1)S^{-1}(k+1) \tag{II.74}$$

and

$$S(k+1) = H(k+1)P(k)H^T(k+1) + R(k+1) \tag{II.75}$$

It is observed from equation (II.73) that the gain K(k+1) is a correction factor that multiplies the difference between the observation $\vec{\mathbf{Y}}$(k+1) and the predicted value of this observation from time k [Bar-Shalom and Fortmann, 1988, ch. 2]. The covariance recursion matrix is then given as

$$\begin{aligned} P(k+1) &= P(k) - K(k+1)S(k+1)K^T(k+1) \\ &= [I - K(k+1)H(k+1)]P(k) \end{aligned} \tag{II.76}$$

where I is the identity matrix.

II.2.7.3.2.2 Linear Estimator: The Kalman Filter

In this section the methods of linear estimation described above (least squares method) for quantities that vary dynamically with time are discussed. Recursive estimators such as the minimum variance or equivalently the minimum mean square error estimator can be utilized for recursive dynamic target tracking. These estimators or recursive filters can estimate the state vector $\vec{\mathbf{X}}$ at time k given a set of observations $\vec{\mathbf{Y}}$, predict an estimate of $\vec{\mathbf{X}}$ at some time (k+1) in the future given $\vec{\mathbf{Y}}$, and uniformize the value estimate $\vec{\mathbf{X}}$ at time prior and after k. The minimum mean square error estimator reduces the variance of the estimate by minimizing the mean square value of the residual or estimation error [Waltz and Llinas, 1990, ch. 6].

The Kalman filter represents a recursive solution to the minimum mean square estimation problem for

The Kalman filter represents a recursive solution to the minimum mean square estimation problem for linear estimation. The Kalman filter will minimize the mean square error as long as the target dynamics and the measurement noise are correctly modelled. Furthermore, this type of filter presents several advantages due to its multiple properties that makes it the best choice for optimum filtering. For example, assuming target manoeuvre and measurement noise, one property is that the gain progression can be chosen automatically so that the same Kalman filter can be used for varying target and measurement environments by modifying a few important parameters. Another property of the Kalman filter is that the gain sequence can automatically adapt to changing detection histories. Finally the Kalman filter can provide a convenient measure of the estimation accuracy through the covariance matrix. This is useful for manoeuvre detection and target tracking [Blackman, 1990, chap 2].

Several books and papers in the literature such as [Kalman, 1960 and 1961] and [Du Plessis, 1967] derive common expressions for the Kalman filtering theory that are required for optimal state estimation. The principal Kalman equations are presented here without derivations. Assuming discrete time and a linear dynamic system, the dynamic difference equation model is given as

$$\vec{X}(k+1) = \Phi(k)\vec{X}(k) + A(k)\vec{W}(k) \tag{II.77}$$

where $\Phi(k)$ is the state transition matrix, $\vec{W}(k)$ is the plant noise with white zero mean sequence with covariance Q(k) and A(k) is the corresponding noise matrix.

When a manoeuvre is involved in the process, then the target process model becomes

$$\vec{X}(k+1) = \Phi(k)\vec{X}(k) + A(k)\vec{W}(k) + B(k)\vec{U}(k) \tag{II.78}$$

where B(k) is the coupling matrix for manoeuvre variable and $\vec{U}(k)$ is the manoeuvre variable vector (acceleration) with covariance matrix L.

The discrete time measurement or observation equation $\vec{Y}_k$ that relates to the state vector $\vec{X}$ is given by equation (II.62). The Gauss-Markov process holds here since the linearity of equations (II.62) and (II.77) or (II.78) leads to the preservation of the Gaussian property of the state and measurement. The discrete time Markov process is a statistical representation of the process in the future given the present state [Blackman, 1990, chap 2; Anderson and Moore, 1979, ch. 2].

The main problem in Kalman filtering is to find an estimate of the state vector $\vec{X}$, that is $\hat{X}$. Assuming that $\vec{X}$ and the observation measurement $\vec{Y}$ are Gaussian, then $\hat{X}$ will also be Gaussian. Thus in a general sense, the problem for estimating $\vec{X}$ is to choose $\hat{X}$ so that the conditional mean $E[(\vec{X} - \hat{X})^2|\vec{Y}]$ is minimized [Du Plessis, 1967]. The solution to this problem is to find the conditional mean of the state vector $\vec{X}$ given the measurement $\vec{Y}^k$, that is [Bar-Shalom and Fortmann, 1988, ch. 2; Anderson and Moore, 1979, ch. 5],

$$\hat{\boldsymbol{X}}(k) = E[\vec{\boldsymbol{X}}(k) \mid \vec{\boldsymbol{Y}}^k] \tag{II.79}$$

where $\vec{Y}^k = \{y(1), y(2), ..., y(n)\}$ and where the associated conditional state error covariance matrix is given as

$$P(k \mid k) = E([\vec{\boldsymbol{X}}(k) - \hat{\boldsymbol{X}}(k \mid k)] [\vec{\boldsymbol{X}}(k) - \hat{\boldsymbol{X}}(k \mid k)]^T \mid \vec{\boldsymbol{Y}}^k) \tag{II.80}$$

Then the estimate posterior to (k+1), that is $\hat{X}(k+1|k+1)$ and its associated covariance $P(k+1|k+1)$, can be computed recursively with the mean prior to (k+1), that is $\hat{X}(k+1|k)$, based on measurement $\vec{Y}(k+1)$ with prior mean $\hat{Y}(k+1|k)$. Given the dynamic plant equation model (II.78) and measurement equation model (II.62) the Kalman filter equations are described below [Bar-Shalom and Fortmann, 1988, ch. 2; Anderson and Moore, 1979, ch. 5].

Applying the expected value $E[\vec{X}(k+1)|\vec{Y}^k]$ on equation (II.78) one finds the "one step" prediction of the state equation as

$$\hat{\boldsymbol{X}}(k+1 \mid k) = \boldsymbol{\Phi}(k)\hat{\boldsymbol{X}}(k \mid k) + B(k)\vec{\boldsymbol{U}}(k) \tag{II.81}$$

that is the predicted estimate at time (k+1) for measurement at time k, and the "one step" prediction covariance is given as

$$P(k+1 \mid k) = \Phi(k)P(k \mid k)\Phi^T(k) + Q(k) \tag{II.82}$$

Taking the expected value $E[\vec{Y}(k+1)|\vec{Y}^k]$ on equation (II.62) at time (k+1), the predicted measurement is obtained as

$$\hat{Y}(k+1 \mid k) = H(k+1)\hat{X}(k+1 \mid k) \tag{II.83}$$

with a measurement prediction covariance given by

$$S(k+1) = H(k+1)P(k+1)H^T(k+1) + R(k+1) \tag{II.84}$$

Then the filter gain is

$$K(k+1) = \Phi(k+1)P(k+1|k)H^T(k+1)S^{-1}(k+1) \tag{II.85}$$

and the predicted estimate or the state update equation that is the predicted estimate at time (k+1) for measurement at time (k+1), where $\vec{Z}(k+1)$ is the residual measurement or innovation of the filter at time (k+1) in equation (II.63),

$$\hat{X}(k+1 \mid k+1) = \hat{X}(k+1 \mid k) + K(k+1)\vec{Z}(k+1 \mid k) \tag{II.86}$$

The covariance of the state update equation at time (k+1) or the covariance update equation is then given as

$$\begin{aligned} P(k+1|k+1) &= P(k+1|k) - K(k+1)S(k+1)K^T(k+1) \\ &= [I - K(k+1)H(k+1)]P(k+1|k) \\ &= [I - K(k+1)H(k+1)]P(k+1|k)[I \\ &\quad - K(k+1)H(k+1)]^T + K(k+1)R(k+1)K^T(k+1) \end{aligned} \qquad \textbf{(II.87)}$$

Note here that the Kalman filter equations (II.84) to (II.87) are similar to the recursive least squares estimator equations (II.73) to (II.76).

The forms for the covariance update equation given above have different numerical properties. The covariance equations given can be chosen for practical implementations depending on the requirements for the filter to be designed. For example, the last equation in (II.87) will ensure that the covariance P will remain both symmetric and positive definite at the expense of some extra computation [Bar-Shalom and Fortmann, ch. 2, 1988]. Other filter implementation techniques that can increase the numerical stability and decrease the computational count are discussed in [Farooq, 1990].

Note here, that some papers in the literature discuss alternative and simple methods to obtain Kalman filter gain equations. For example, [Chan and Couture, 1991] suggests an alternate set of equations for the exact computation of the Kalman gains when there is no manoeuvring input noise and measurements in positions and velocity. These recursive equations are applied when the implementation of the standard Kalman filter is not possible due to real-time restrictions. For the case of manoeuvring input noise, the same gains can approximate optimal gains with minor degradation in performance.

Another approach is given by [Baheti, 1986] to calculate the gains. He developed an approximate gain computation algorithm to determine the filter gains. His approach was to compute the gains for tree uncoupled filters and multiply them by a Jacobian transformation determined from the target position and orientation. He has shown that the method proposed was nearly identical to the extended Kalman filter discussed below with computation requirements reduced by four.

In summary, the Kalman filter is the simplest possible linear state estimation filter. It represents the solution to recursive calculations of the linear Gaussian statistic case, i.e., the mean and variance [Bar-Shalom and Fortmann, 1988, ch. 3]. The Kalman filter block diagram concerning the above equations is shown in Figure II.14.

[illegible]

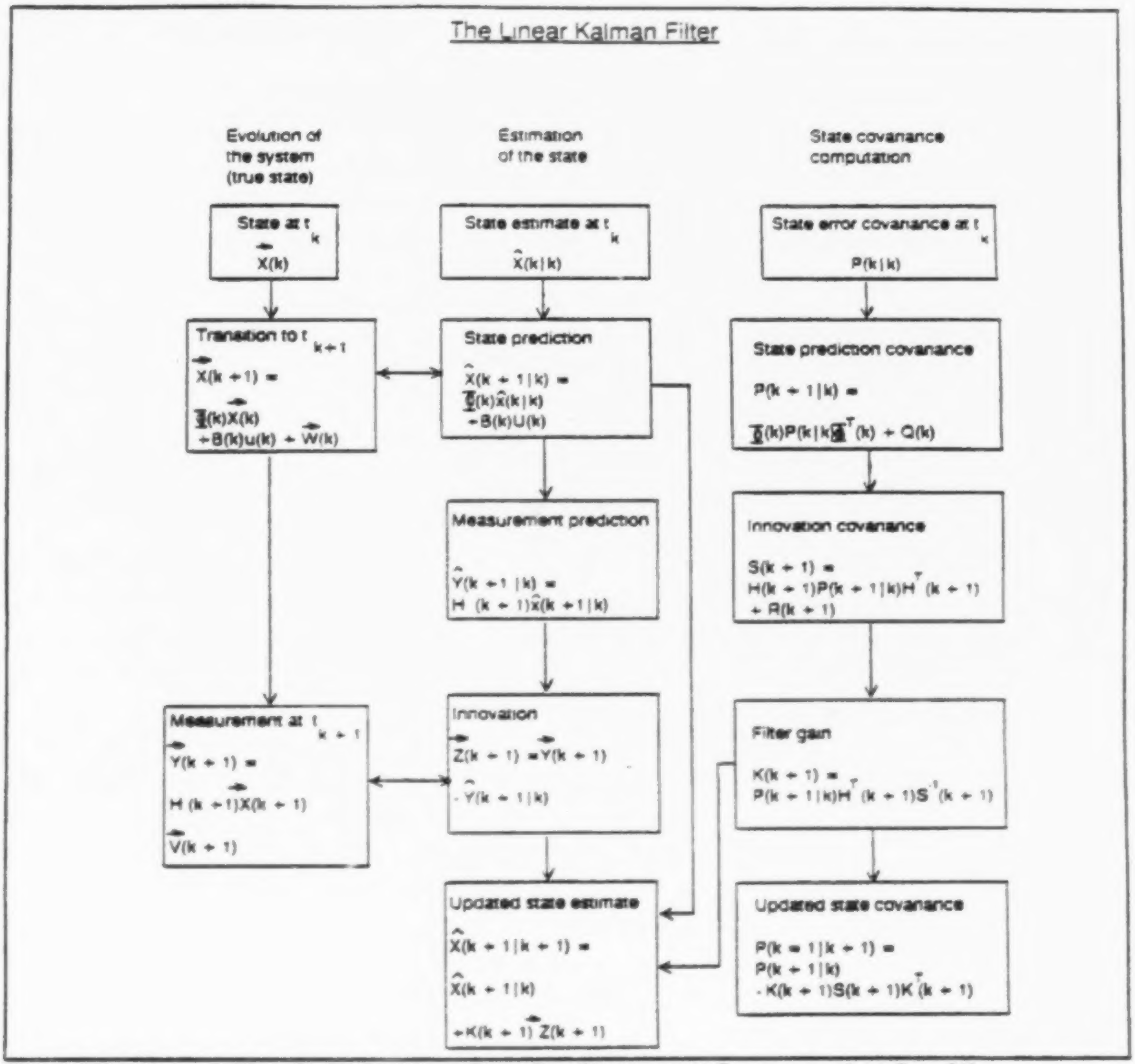
The Linear Kalman Filter
Evolution of the system (true state)
Estimation of the state
State covariance computation
State at t_k
$\vec{X}(k)$
State estimate at t_k
$\hat{X}(k|k)$
State error covariance at t_k
$P(k|k)$
Transition to t_{k+1}
$\vec{X}(k+1) = \Phi(k)\vec{X}(k) + B(k)u(k) + \vec{W}(k)$
State prediction
$\hat{X}(k+1|k) = \Phi(k)\hat{x}(k|k) + B(k)U(k)$
State prediction covariance
$P(k+1|k) = \Phi(k)P(k|k)\Phi^T(k) + Q(k)$
Measurement prediction
$\hat{Y}(k+1|k) = H(k+1)\hat{x}(k+1|k)$
Innovation covariance
$S(k+1) = H(k+1)P(k+1|k)H^T(k+1) + R(k+1)$
Measurement at t_{k+1}
$\vec{Y}(k+1) = H(k+1)\vec{X}(k+1)$
$\vec{V}(k+1)$
Innovation
$\vec{Z}(k+1) = \vec{Y}(k+1) - \hat{Y}(k+1|k)$
Filter gain
$K(k+1) = P(k+1|k)H^T(k+1)S^{-1}(k+1)$
Updated state estimate
$\hat{X}(k+1|k+1) = \hat{X}(k+1|k) + K(k+1)\vec{Z}(k+1)$
Updated state covariance
$P(k+1|k+1) = P(k+1|k) - K(k+1)S(k+1)K^T(k+1)$

Figure II.14. Kalman Filter Block Diagram (From Bar-Shalom and Fortmann, chap.2 p. 61)

The above equations were given for discrete time, linear stochastic systems. For non-linear systems, the suboptimal filter or equivalently the extended Kalman filter can be used for state estimation. A non-linear system may result from the non-linearity in the description of the tracking problem. The non-linearity problem can thus be approximated by a series expansion of the non-linear dynamics and measurement equations [Hassab, 1990, ch. 16; Bar-Shalom and Fortmann, 1988, ch. 3].

For non-linear systems, equations (II.62) and (II.77) can be written in the following general forms [Bar-Shalom and Fortmann, 1988, ch. 2; Anderson and Moore, 1979, ch. 8]

$$\vec{X}(k+1) = \Phi[k,\vec{X}(k)] + A(k)\vec{W}(k) \tag{II.88}$$

$$\vec{Y}(k) = h[k,\vec{X}(k)] + \vec{V}(k) \tag{II.89}$$

where the time argument k indicates that the vector valued functions Φ and h are time varying.

Assuming the above equations, the non-linear functions in (II.88) can be expressed in a Taylor series around $\hat{X}(k|k)$ with terms up to the first or second order to get the predicted state $\hat{X}(k+1|k)$ and the associated covariance P(k+1|k). This leads to the first or second order extended Kalman filter respectively. The solution for the extended Kalman filter gain, state update and covariance update is identical to those from the linear filters equations (II.84) to (II.87) except that H(k+1) is replaced by $h_x(k+1)$, where

$$h_{\vec{X}}(k+1) = \left[\nabla_{\vec{X}} h_{\vec{X}}{}^{T}(k+1,\vec{X})\right]^{T}_{\vec{X}=\hat{X}(k+1|k)} \tag{II.90}$$

is the Jacobian of the function h.

Because of the complexity of the non-linear transformations of the second order equations, other methods can be used to implement extended Kalman filter. One method is to use the iterative minimization of the cost function $J[\vec{X}(k+1)]$ by using the Newton-Raphson algorithm. This will allow the determining of the estimate $\hat{X}(k+1|k+1)$. The recursive equations for the iterated extended Kalman filter are given below [Bar-Shalom and Fortmann, 1988, ch. 3]

$$\begin{aligned}\hat{\mathbf{x}}^{i+1}(k+1|k+1) = {} & \hat{\mathbf{x}}^{i}(k+1|k+1) \\ & + P^{i}(k+1|k+1)(H^{i}(k+1))^{T}R^{-1}(k+1)\{\vec{\mathbf{Y}}(k+1) \\ & - h[(k+1),\hat{\mathbf{x}}^{i}(k+1|k+1)]\} \\ & - P^{i}(k+1|k+1)P^{-1}(k+1|k)[\hat{\mathbf{x}}^{i}(k+1|k+1) \\ & - \hat{\mathbf{x}}(k+1|k)]\end{aligned} \tag{II.91}$$

where

$$H^{i}(k+1) = h_{\mathbf{x}}[(k+1),\hat{\mathbf{x}}^{i}(k+1 \mid k+1)] \tag{II.92}$$

with the starting iteration for i=0

$$\hat{\mathbf{x}}^{0}(k+1 \mid k+1) = \hat{\mathbf{x}}(k+1 \mid k) \tag{II.93}$$

which yields to $\hat{X}^{1}(k+1|k+1)$, which is the same as the first order non-iterated extended Kalman filter.

The corresponding iterated covariance is then given as

$$P^{i}(k+1 \mid k+1) = P(k+1 \mid k) - P(k+1 \mid k)(H^{i}(k+1))^{T} \times [H^{i}(k+1)P(k+1 \mid k)(H^{i}(k+1))^{T} + R(k+1)]^{-1} H^{i}(k+1)P(k+1 \mid k) \tag{II.94}$$

Other schemes can be used for improving the performance of the extended Kalman filter as suggested by [Song and Speyer, 1985] or [Weiss and Moore, 1980]. Examples of the performance of the extended Kalman filters can be found in [Spingarn, 1987].

Furthermore, [Spingarn, 1987] derives the general equations for the extended Kalman filter and the iterated Kalman filter for the application to the passive position location problem.

II.2.7.3.3 Fixed Coefficient Gain Filters

In adaptive Kalman Filtering theory discussed above, it was shown that the filter gain was updated according to the state error covariance matrix P(k|k). Then the filter gain was used to update the state estimate and the covariance matrix. This process done recursively resulted in adaptive gain for filtering.

Other types of filters for time invariant systems such as the α-β and α-β-γ filters can be used for target state estimation. These type of filters are used only when position measurements are available, i.e., equation (II.62), where H = [0 1] for the two-dimensional case and H = [1 0 0] for the three-dimensional case with measurement covariance σ^2_v. The estimate of $\vec{X}$ has the form [Bar Shalom-and Fortmann, 1988, ch. 2]

$$\begin{aligned} \hat{\mathbf{x}}(k+1 \mid k+1) &= \hat{\mathbf{x}}(k \mid k) + K\vec{\mathbf{z}}(k+1 \mid k) \\ &= \hat{\mathbf{x}}(k \mid k) + \begin{bmatrix} \alpha \\ \beta/T \\ \gamma/T^2 \end{bmatrix} \vec{\mathbf{z}}(k+1 \mid k) \end{aligned} \tag{II.95}$$

where $\vec{Z}(k+1|k)$ is the residual as defined before, T is the sampling interval, and the coefficients α, β and γ are dimensionless constant filter gains for the position, velocity and acceleration components of the state, respectively [Bar-Shalom and Fortmann, 1988, ch. 2]. The choice of fixed coefficient gains depends on the required performance of the filter. For example, a less responsive filter will result by decreasing the coefficients, but will improve measures of performance for random noise input. Therefore, the choice of gains for this type of filter must reflect an overall compromise between noise and dynamic performance [Blackman, 1990, ch. 2].

II.2.7.3.3.1 The α-β Filter

The plant equation (II.77) is used for optimal α-β filters with transition matrix Φ being equal to

$$\Phi = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \tag{II.96}$$

The steady state values of the components of the state estimation covariance matrix are denoted as [Bar-Shalom and Fortmann, 1988, ch. 2]

$$P = \lim_{k\to\infty} P(k \mid k) = \lim_{k\to\infty} P(k+1 \mid k+1) = \begin{bmatrix} p_{11} & p_{12} \\ p_{12} & p_{22} \end{bmatrix} \tag{II.97}$$

with the components of the one step prediction covariance given as

$$M = \lim_{k\to\infty} P(k+1 \mid k) = \begin{bmatrix} m_{11} & m_{12} \\ m_{12} & m_{22} \end{bmatrix} \tag{II.98}$$

and the filter gain given as

$$K = \lim_{k \to \infty} K(k) = \begin{bmatrix} g_1 \\ g_2 \end{bmatrix} = \begin{bmatrix} \alpha \\ \beta / T \end{bmatrix} \tag{II.99}$$

The set of equations for the innovation covariance S, the filter gain K and the covariance P are given respectively as

$$\begin{aligned} S &= HMH^T + \sigma_v^2 \\ K &= MHS^{-1} \\ P &= (I - KH)M \end{aligned} \tag{II.100}$$

where Φ^{-1} is the same as in (II.96) except with a minus sign before the sampling interval T in the matrix, and

$$Q = \begin{bmatrix} T^4/4 & T^3/2 \\ T^3/2 & T^2 \end{bmatrix} \sigma_w^2 \tag{II.101}$$

The covariance Q corresponds to a piecewise constant white process noise model with covariance process noise W(k) as σ^2_w, that is the acceleration over each sampling period and independent from period to period. Thus the state estimation covariances are found with the following equations [Bar-Shalom and Fortmann, 1988, ch. 2]

$$p_{11} = (1-g_1)m_{11} = g_1\sigma_v^2 = \alpha\sigma_v^2 \tag{II.102}$$

$$p_{12} = (1-g_1)\,m_{12} = g_2\sigma_v^2 = \frac{\beta}{T}\sigma_v^2 \qquad \text{(II.103)}$$

$$\begin{aligned} p_{22} &= \left[\frac{g_1}{T} + \frac{g_2}{2}\right] m_{12} \\ &= \left[\frac{\beta}{T^2}\,\frac{(\alpha-\beta/2)}{(1-\alpha)}\right]\sigma_v^2 \end{aligned} \qquad \text{(II.104)}$$

with

$$m_{22} = \frac{g_1 m_{12}}{T} + \frac{T^2\sigma_w^2}{2} = \left[\frac{g_1}{T} + \frac{g_2}{2}\right] m_{12} \qquad \text{(II.105)}$$

Therefore, all components can be found with the above equations. The quantities α and ß can be found according to the target manoeuvring index δ [Kalata, 1984], i.e.,

$$\begin{aligned} \beta &= \frac{\delta^2 + 4\delta - \delta\sqrt{\delta^2 + 8\delta}}{4} \\ \alpha &= \frac{\delta^2 + 8\delta - (\delta+4)\sqrt{\delta^2 + 8\delta}}{8} \end{aligned} \qquad \text{(II.106)}$$

where δ is given by

$$\delta^2 = \frac{\beta^2}{1-\alpha} = \frac{\beta^2}{(1-\sqrt{\beta/2})^2} = \frac{T^4\sigma_w^2}{\sigma_v^2} \qquad \text{(II.107)}$$

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where σ_w is the position process noise standard deviation. [Bar-Shalom and Fortmann, 1988, ch.2] show the plots for the gains α and β as function of δ. Those plots help to chose the proper gains required in designing the filter.

II.2.7.3.3.2 The α-β-γ Filter

For this filter, equation (II.77) is used with the following transition matrix

$$\Phi = \begin{bmatrix} 1 & T & \frac{T^2}{2} \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix} \qquad \text{(II.108)}$$

The covariance of the process noise which is assumed to be a piecewise constant acceleration increment is given by [Bar-Shalom and Fortmann, 1988, ch. 2]

$$Q = \begin{bmatrix} \frac{T^4}{4} & \frac{T^3}{2} & \frac{T^2}{2} \\ \frac{T^3}{2} & T^2 & T \\ \frac{T^2}{2} & T & 1 \end{bmatrix} \sigma^2_v \qquad \text{(II.109)}$$

Then the optimal equations for steady state filter gains are given as

$$\delta^2 = \frac{\gamma^2}{4(1-\alpha)} = \frac{T^4 \sigma^2_v}{\sigma^2_v} \qquad \text{(II.110)}$$

and

$$\begin{aligned}\beta &= 2(2-\alpha) - 4\sqrt{1-\alpha}\\ \alpha &= \sqrt{2\beta} - \beta/2\\ \gamma &= \beta^2/\alpha\end{aligned} \tag{II.111}$$

and the corresponding updated state covariances are given by

$$\begin{aligned}p_{11} &= \alpha\sigma^2_v\\ p_{12} &= \frac{\beta}{T}\sigma^2_v\\ p_{13} &= \frac{\gamma}{T^2}\sigma^2_v\end{aligned} \tag{II.112}$$

$$\begin{aligned}p_{22} &= \frac{8\alpha\beta + \gamma(\beta-2\alpha-4)}{8T^2(1-\alpha)}\sigma^2_v\\ p_{23} &= \frac{\beta(2\beta-\gamma)}{4T^3(1-\alpha)}\sigma^2_v\\ p_{33} &= \frac{\gamma(2\beta-\gamma)}{4T^4(1-\alpha)}\sigma^2_v\end{aligned} \tag{II.113}$$

[Bar-Shalom and Fortmann, 1988, ch. 2] also show the plots for the gains α, ß and γ as function of δ.

II.2.7.4 Adaptive Estimation

The adaptive estimation is the process of minimizing error values computed by an approximator given the measured data collected. The adaptive estimation is normally used for detecting and tracking target manoeuvre. For example, the Kalman filter is usually used for optimal filtering to detect and predict the manoeuvre. In a general sense, the filter may assume a particular model. When a manoeuvre occurs, an error is developed in comparison with the assumed model by the filtering process and the detection occurs. The error correction for the state estimate is then created, to compensate for the assumed manoeuvre. After detection and correction phases, the filter parameters (such as the filter gain) are adjusted so as to adapt to the new manoeuvre model [Hassab, 1990, ch. 16].

Different approaches for adaptive state estimation exist in the literature. An extensive discussion on adaptive filtering for target manoeuvre will be given in section II.2.8. Three general approaches for adaptive filtering to target manoeuvre will be outlined. It will illustrate Kalman filtering for adaptive state estimation. The approaches are the manoeuvre detection and parameter adjustment, the manoeuvre detection and state augmentation, and several filters in parallel, working simultaneously.

II.2.7.5 UDU^T Matrix Forms for Kalman Filter

The U-D factorization method is another technique used in data processing algorithm. The U-D factorization of the Kalman filter update algorithm is usually used for both computational savings and reduction in computer storage requirements. As discussed before, estimation problems were handled using Kalman's sequential covariance estimation formulation. The formulation proposed using U and D matrices is to perform triangular factorization [Bierman, 1977, ch. 5].

Recursion methods have been developed for U and D, where $P=UDU^T$ with U upper triangular and D diagonal. It was found that computations with triangular matrices involve fewer arithmetic operations. Furthermore, this type of factorization avoids time consuming scaler square roots [Bierman, 1977, ch. 5].

With equations (II.62) and (II.77) the covariance update equations in U-D form are expressed as [Bierman, 1977, ch. 5]

$$\begin{aligned} P(k+1|k+1) &= U(k+1|k+1)\,D(k+1|k+1)\,U^T(k+1|k+1) \\ &= U(k+1|k)\,[D(k+1|k) - S^{-1}(k+1) \\ &\quad \times [D(k+1|k)\,U^T(k+1|k)\,H(k+1)] \\ &\quad \times [D(k+1|k)\,U^T(k+1|k)\,H(k+1)]^T]\,U^T(k+1|k) \end{aligned} \tag{II.114}$$

with the gain given as

$$K(k+1) = U(k+1 \mid k)D(k+1 \mid k)U^T(k+1 \mid k)H(k+1)S^{-1}(k+1) \quad \textbf{(II.115)}$$

keeping in mind here that U is a positive definite matrix, non-singular and triangular, and D is a positive definite diagonal matrix. The other parameters such as H and S remain as before.

There are some computational advantages in using the covariance representation in UDU^T form view. These are good: numerical stability since the matrices U and D are positive definite, the reduction of the number of computational steps in the report to track correlation test loop, and good numerical accuracy with single precision required for advanced sensors can be accomplished [Bierman, 1977, ch. 5] [Yannone, 1988].

II.2.7.6 Other Filtering Techniques

There are other filtering techniques that can be applied to Kalman filtering equations to optimize computational efficiency, improve numerical stability and enhance the effective precision. The discussion that follows next is about the modified spherical coordinate filter.

II.2.7.6.1 Modified Polar Coordinates Filter

Another type of filter for target tracking is described by [Stallard, 1987]; this is the Modified Spherical Coordinate (MSC) filter. This type of filter is used to reduce observability problems, range bias and bad covariance condition problems. The tracking is performed with angle measurements. The six state variables are two angles, their derivatives, inverse range and range-rate over range, which are transformable into cartesian position and velocity.

The state vector in the MSC coordinate for a six state filter is given as

$$\vec{X} = \begin{bmatrix} \beta & \theta & \frac{1}{r} & \dot{\beta} & \dot{\theta} & \frac{\dot{r}}{r} \end{bmatrix}^T \qquad \text{(II.116)}$$

where β and θ are azimuth and elevation angles, $\dot{\beta}$ and $\dot{\theta}$ are their respective derivatives and r is the range.

The state estimates are transformed into cartesian coordinates for simplicity and accuracy for state estimate prediction [Aidala and Hammel, 1983]. Before prediction, the estimated relative cartesian position and velocity components are computed from their updated MSC counterparts. Then the update equations are reconverted into the MSC form, that is $\hat{\beta}$ $\hat{\theta}$ and other state estimated variables.

The measurement noise $\vec{V}$ in equation (II.62) is assumed to be white and Gaussian with covariance matrix R. The residual vector is then given as [Stallard, 1987]

$$\hat{Z}(k+1) = \hat{Y}(k+1) - [\hat{\beta} \;\; \hat{\theta}]^T(k+1 \mid k) \qquad \text{(II.117)}$$

Thus the update estimate in MSC is found as the sum of the predicted estimate plus the Kalman gain matrix terms times the residual, i.e.,

$$\hat{X}(k+1 \mid k+1) = \hat{X}(k+1 \mid k) + K(k+1)\hat{Z}(k+1) \qquad \text{(II.118)}$$

where the computation of the covariance propagation and Kalman gain are done in MSC [Stallard, 1987].

II.2.8 Target Model (Type of Manoeuvre) Identification Analysis

II.2.8.1 Introduction

This section presents key AAW target manoeuvre characteristics of targets which are threats to AAW platforms and three filtering techniques for detecting and tracking these manoeuvring targets.

These three different techniques found in the literature for detection and tracking manoeuvring targets are examined. The discussions on these techniques are based on the Kalman filtering theory introduced previously.

II.2.8.2 AAW Target Manoeuvre Kinematic Characteristics

There are several types of manoeuvres that can be identified specific to different weapons and aircraft utilized. Several missiles and aircraft are given in [Janes, 1988, 18th ed.] with their corresponding manoeuvres. Shipborne surface to surface weapons, shipborne surface to air weapons and aircraft air to surface missiles can be considered as threats to surface ships. Among these threats, three general types of manoeuvres are of interest. These manoeuvres are described in the classified Task I Report [Paramax, 1991, doc. # 112000001], the NATO AAW System Requirements Staff Target [NAAWS, 1987] report, and in the unclassified [Janes, 1988, 18th ed.] book. The general types of manoeuvres are:

1. the long range high diving manoeuvre
2. the short range manoeuvre
3. and the seaskimmer type of manoeuvre.

The first type of manoeuvre may result from a missile capable of a long range flight at supersonic speed and at high altitude diving steeply onto the target. The second type of manoeuvre may result from a missile launched from a platform, generally flying at subsonic speed at low or medium altitude, diving onto the target. Finally, the third type of manoeuvre may result from a missile flying at low altitude and following the earth's curvature, then performing a pop-up manoeuvre before impacting onto a target. The supersonic high speed type seaskimmer missile may fly from medium to long range distance at medium altitude, and the subsonic medium speed type seaskimmer may fly from short to medium range distances at a lower altitude [Janes, 1988, 18th ed.]. The kinematic characteristics for these types of manoeuvres can be found in [Paramax, 1991, doc. # 112000001] Task I Report and the NATO AAW System Requirements Staff Target [NAAWS, 1987] report Appendix I to Annex I.

Different types of manoeuvres, such as those mentioned above, as well as manoeuvring aircraft, can be detected and then tracked using sophisticated filtering techniques. These filters can give optimal estimations of the position velocity and acceleration of a moving target from the data provided by sensors.

Several techniques for detecting and tracking manoeuvring targets are suggested in the next subsection. The Kalman filter implementations suggested from the literature are responsive for the detection and tracking of manoeuvres from the threats with which the frigates are faced. The Kalman filtering discussed is for:

- The detection and tracking of slow motion target manoeuvres (II.2.8.3.3.2)
- The detection and tracking of a very rapid target manoeuvre that can occur during the course of travel (II.2.8.3.3.3)
- Rapid manoeuvre detection at high measurement frequency (II.2.8.3.3.4)
- A highly manoeuvring target in a clutter environment (II.2.8.3.3.4)
- The detection and tracking of multiple manoeuvring targets (II.2.8.3.3.5).

The following section includes the description of different filtering techniques and tracking algorithms identified in the surveyed literature for detecting and estimating kinematic variables of manoeuvring targets.

II.2.8.3 Adaptive Filtering And Target Manoeuvre Models

In most common cases tracking algorithms use some practical models of target motion in order to estimate the present and future target kinematic quantities such as the position, velocity and in certain cases, acceleration. Target kinematic models are generally assumed to be well known physical laws such as straight lines, circles, ballistics, etc. When there is an unpredicted change in the assumed target motion model (manoeuvre), the tracking algorithm will detect the error created by this change and correct the situation to adapt itself to this new change or new tracking model [Bar-Shalom and Fortmann, 1988, ch. 1], [Blackman 1986, ch. 2].

There are different approaches in the literature for handling manoeuvre detection and manoeuvre adaptive filtering. For practical purposes, the most general approaches are examined in this section. They are the use of:

1. Manoeuvre detection and parameter adjustment
2. Manoeuvre detection and state augmentation
3. Several parallel filters.

Other approaches also use a combination of two or three of these methods. Target manoeuvre algorithms mainly utilize the Kalman filter since it provides optimum estimates of target position and velocity [Blackman 1986, ch. 2],[Waltz and Llinas, 1990, ch. 6].

The first approach is to modify the Kalman filter parameters after manoeuvre detection. This adaptive technique results in a filter capable of monitoring its own performance and making appropriate parameter adjustments when performances deteriorate. One of the methods commonly used for manoeuvre detection is to examine the time history of the residual [Blackman 1986, ch. 2]. This will be examined later in this section.

The second approach that will be discussed is the augmentation of the filter state model upon manoeuvre detection. When there is no manoeuvre, a constant velocity target model is assumed. After manoeuvre detection, tracking is performed with an augmented state model that uses an acceleration state. This method requires the storage of previous measurements, which are used for filter reinitialization after manoeuvre detection. The augmented state model is used until the magnitude of the acceleration estimate is determined to be insignificant, then use of the initial state modes is resumed [Blackman 1986, ch. 2].

In the third approach, multiple Kalman filters can be used to operate in parallel simultaneously on the measurement sequence, each with a differing manoeuvre model. Thus the filter with the best output can be chosen. The simplest example for this method is to have just two Kalman filters in which one filter assumes a straight line motion while the other is matched to a worst case manoeuvre condition. The non-manoeuvre case is assumed until a detector is triggered. Then the exchange of filter is made to the one with manoeuvre ability. Thus upon manoeuvre detection, adaptation and correction are applied together by switching to a more responsive filter whose output is more representative of the true target state [Blackman 1986, ch. 2]. Several variations of this concept will be discussed below.

In the next two subsections the manoeuvre detection and parameter adjustment and manoeuvre detection and state augmentation approaches are introduced. These approaches are the elemental theory often required for the use of several parallel filters approach. These two apporches were developed in the begining of the 1980's.

This approach usually requires the manoeuvre characteristics of the target for modelling. The definitive work in parallel filtering began in the mid 60's, and is still in use today. The discussion of this approach is also provided.

In the literature, it was found that throughout the years several authors preferred to develop adaptive filtering theory using a bank of several Kalman filters for various reasons. Some authors preferred to get optimum and quick results for tracking a manoeuvring target that apparently require large computational loads. These methods are usually costly.

Other authors found new methods to reduce computational loads using suboptimal adaptive filtering methods or found ways to reduce the memory space because of the physical limits of computer memories. Some developed new algorithms that would minimize the number of filters to be used for adaptive filtering in a cost effective manner. These algorithms are capable of tracking manoeuvring targets rapidly and efficiently. A discussion on the topic is given below. The adaptive filtering techniques in the literature throughout the years can still be applicable today.

II.2.8.3.1 Parameter Adjustment and Adaptive Kalman Filtering for Manoeuvre Detection

[Chan, Hu and Plant, 1979] present an algorithm (CHP algorithm) to detect and track manoeuvring targets using a Kalman filter and a detector scheme. The advantage of this method is that there is no requirement for a priori knowledge of the manoeuvre characteristics of the target, and the estimation process is independent of target types. The tracking scheme presented is an estimation of the acceleration inputs over a sliding window from the residuals of the filter, and used these estimates to update the parameters of the Kalman filter.

The principle of this method is to estimate the input acceleration $\vec{U}$ (i.e. $\hat{U}$) in equation (II.78) over a sliding window (k+j) from the residual $\vec{Z}_{k+j}$ of the Kalman filter given in equation (II.63) when a manoeuvre occurs. It is assumed that $\vec{U}_{k+j} = \vec{U}$ is a constant over that interval. If the consistency of $\vec{U}_{k+j}$ changes over that interval, the estimator gives the best estimate for the different inputs in the least square sense over that interval. Thus the general least square estimate of $\vec{U}$ is calculated as $\hat{U}$ with its associated covariance matrix L [Chan, Hu and Plant, 1979].

Thus $\hat{U}$ is used to remove the bias developed in the Kalman filter due to target manoeuvre. The update estimate at time (k+λ+1)T is then given as [Chan, Hu and Plant, 1979]

$$\tilde{X}_{(K+\lambda+1)} = \vec{X}_{(K+\lambda+1)} + M(\hat{U} - \vec{U}) \qquad \text{(II.119)}$$

assuming that $\vec{U}_{k+j} = \vec{U}$ for j = 1, where M is a coupling matrix of full rank and s is the number of measurements.

Since $\tilde{X}_{k+\lambda+j}$ is updated by $\hat{U}$, there is an increase in the variance. Thus the covariance matrix P in equation (II.87) must be updated accordingly. The new equation becomes $P_{(k+\lambda+1)}$. This will cause a corresponding increase in the Kalman gain [Chan, Hu and Plant, 1979].

The detection scheme is applied by using the norm of $\hat{U}$. Then a test statistic which is chi-square distributed is computed using the norm of $\hat{U}$ and compared against a threshold value. If the threshold is exceeded the updating process occurs. Therefore the probability of detection or false alarm can be obtained from statistical tables [Chan, Hu and Plant, 1979].

Finally, the CHP algorithm shows the integration and performance of the least square estimation and the detector into a tracking scheme. [Chan, Hu and Plant, 1979] shows the computed results of the root mean square (rms) values of the estimation errors and the effectiveness of the tracker in the constant course and speed segment of the trajectories. In the manoeuvre segment, the root mean square (rms) estimation errors are found to be higher, and the scheme presents, once in a while, a time delay in detecting the manoeuvre. The tracking was reduced during manoeuvring by lowering the threshold at the expense of false alarm probabilities.

II.2.8.3.2 State Augmentation Adaptive Kalman Filtering for Manoeuvre Detection

[Bar-Shalom and Birmiwal, 1982] presents another type of algorithm to detect and track manoeuvring targets used with a simple Kalman filter. The principle is that the tracking filter is in normal operation mode when the target is not manoeuvring. Then a detection scheme is utilized to detect the manoeuvre and a different state model is used by the filter. Thus new state components are added. The filter is then reinitialized for the new manoeuvring model once the manoeuvre is detected. The magnitude of the manoeuvre detected is then used to get an estimate for the extra state components, and corrections are made on the other state components. The tracking is done with the augmented state model until another decision is made. Then the normal model takes place. This method presents the advantage that it can be implemented without a priori knowledge of the manoeuvring characteristics of the target [Bar-Shalom and Birmiwal, 1982].

When there is no manoeuvre the target is modelled as a constant velocity object in a plane, with some process noise as in equation (II.77). The state vector in a cartesian coordinate is represented as $\vec{X}$ = [X, $\dot{X}$ Y, $\dot{Y}$] where X, $\dot{X}$ Y, $\dot{Y}$ represent the position and velocity in X and Y respectively. In the manoeuvring model the new state vector is given as $\vec{X} = [X, \dot{X}, Y, \dot{Y}, \ddot{X}, \ddot{Y}]$ where an acceleration component has been added [Bar-Shalom and Birmiwal, 1982].

To detect the manoeuvre, a fading memory average $\mu(k)$ of the innovation from an estimator based on the quiescent model [Bar-Shalom and Birmiwal, 1982] is computed, where the manoeuvre is tested over an effective window length Δ. Thus the manoeuvre exists if $\mu(k)$ exceeds a certain threshold. Then the estimator switches from the quiescent model to the manoeuvring model. The scheme for returning to the quiescent model is to compare the estimate accelerations to their standard deviations. If they are not statistically important, the manoeuvre hypothesis is thus rejected. The test statistics for significance of the acceleration estimate is determined with the estimate acceleration components and the corresponding block from the covariance matrix over the effective window length [Bar-Shalom and Birmiwal, 1982].

Upon manoeuvre detection the state estimate equation $\hat{X}(k)$ and its associated covariance matrix P must be modified over the effective window length, that is $\hat{X}(k-\Delta|k-\Delta)$ and $P(k-\Delta|k-\Delta)$. These equations designate the initialization of the Kalman filter based on the manoeuvring model for time $(k-\Delta)$ [Bar-Shalom and Birmiwal, 1982].

[Bar-Shalom and Birmiwal, 1982] have presented the same simulation models for target manoeuvring as in the [Chan, Hu and Plant, 1979] paper to compare their results. [Bar-Shalom and Birmiwal, 1982] show that the two trackers appear to be equally effective in the uniform track of the target trajectories, but their algorithm has a lower average error during the manoeuvring period. They show statistical improvements of their algorithm over the CHP algorithm in position over all the intervals considered and in velocity in two intervals. Finally, their algorithm is found to have lower computational running time [Bar-Shalom and Birmiwal, 1982].

II.2.8.3.3 Multiple Filtering for Tracking a Manoeuvring Target

II.2.8.3.3.1 Basic Principles for Parallel Filtering

In 1965 Magill proposed a nice method to introduce adaptive Kalman filtering. A bank of N parallel filters are operating simultaneously on the observed measurement sequence $\vec{Y}_k$. Each filter in the bank utilizes a different target process model. The target process model is divided into N possible manoeuvre-related hypotheses $\alpha_1, \alpha_2, \ldots, \alpha_n$. These hypotheses correspond to N possible times of manoeuvre since the starting time of the manoeuvre is the critical parameter to estimate. Each hypothesized filter corresponds to a different time at which the manoeuvre is assumed to occur. Therefore the n^{th} Kalman filter is governed by equation (II.78) when there is a manoeuvre or by equation (II.77) otherwise. The Kalman filter observed to have the best a posteriori probability is the optimum Kalman filter [Bogler, 1987].

Magill developed an expression for the a posterior probability that the α_n Kalman filter is the correct one. The weighting coefficients $\{P(\alpha_n|\vec{Y}_k)$: $n = 1, 2, ..., L$; $\vec{Y}_k = y(1), y(2), ..., y(k)\}$ were determined by applying Bayes rule and the elemental process was described by the multirative Gaussian density function. These coefficients are thus determined by simple non-linear operations on the observed data where the optimal adaptive estimate is an appropriately weighted summation of conditional estimates, which are formed by a set of filters [Magill, 1965].

Therefore Magill's method provided a way to both detect and adjust for the target manoeuvre. The Kalman filter with the maximum a posterior probability is the one that minimizes the sum of the weighted square of all its past residuals. Its corresponding output $\hat{\vec{X}}_k^n$ is the single best estimate of target state $\vec{X}_k$ [Bogler, 1987].

II.2.8.3.3.2 A Tracking Scheme for Target Manoeuvre

Another approach involving multiple Kalman filter estimation was used by [Thorp, 1973]. His approach is to model manoeuvring target motion by introducing a binary random variable $\tau(k)$ in the target state equation (II.77). This binary random variable is added in the driving noise of equation (II.77), which is assumed to be a white Gaussian sequence. Because of the non-linear processing of observations, he suggests a special case to obtain equations for the non-linear filter. When the time of possible manoeuvre is known, this special case suggests a scheme for tracking and manoeuvring detection for a class of manoeuvring targets. The filter involves combining Kalman filter estimates using coefficients obtained from a likelihood ratio formed from the observation. The likelihood ratio is also used to estimate the occurrence of manoeuvre. The likelihood ratio is computed for the hypothesis as to whether or not a manoeuvre filter is used. When the target is not manoeuvring a standard Kalman filter is used. If it is decided that a manoeuvre did not occur, the best state estimate is a weighted sum of Kalman filters. The optimal filter estimate is a weighted combination of two Kalman filter estimates with weights depending on the likelihood ratio for the detection of a manoeuvre [Thorp, 1973].

All the quantities required to compute the equations developed by Thorp can be obtained from the

Kalman filters. The minimum variance estimate $\vec{X}_s(k+n|k-n)$ is found to be a convex combination of the two Kalman filter estimates with the coefficients depending on all observations since the possible manoeuvre. This equation was seen as a special case involving Kalman filter estimates of results obtained in [Middleton and Esposito, 1968] and [Magill, 1965].

The tracking system for target manoeuvre proposed by [Thorp, 1973] involves a tracker with two modes of operation. The first is a single Kalman filter for simple target motion and the second is the filter that provides optimal estimate which combines two estimates. The proposed tracking scheme for target manoeuvre works on the assumption that the data rate is low enough to allow modelling a manoeuvre as a discrete phenomenon as in the case of some sonar applications. The filtering scheme is recursive and involves moderate non-linear operations on variables available in the Kalman filter [Thorp, 1973].

II.2.8.3.3.3 Tracking Schemes for Rapid Target Manoeuvre

[Ricker and Williams, 1978] suggest higher speed tracking target manoeuvre. For the process proposed in that paper, the target is assumed to experience a very rapid manoeuvre that occurs only rarely during the course of travel. This technique requires the generation of a continuously expanding set of Kalman filters responding to a continuously expanding set of options available to the manoeuvring target [Ricker and Williams, 1978]. The proposed implementation limited the expansion to a discrete set of values for the manoeuvre variables. This produced a tree structure with the manoeuvre represented by a discrete set of values. Because of this set of values, they establish that an expansion of M^2 filters can be avoided by choosing a compromise suboptimum implementation that uses an average value for the manoeuvre variable, making it necessary to carry along only M Kalman filters at most. The main advantage of their approach is that it provides a continuous estimate of the manoeuvre variables in a recursive manner without an assumption of the statistical nature of the manoeuvre and without the penalties of a detecting mechanism for the manoeuvre [Ricker and Williams, 1978].

Their method treats the residual as a multirative Gaussian density, and through the use of the Bayes rule, they develop the probabilities associated with the prescribed set of discrete manoeuvres. The average manoeuvre value, which may be zero when there is no manoeuvre, is computed and used to update the state variables, thereby constraining the growth of the conceptual tree [Ricker and Williams, 1978].

The above method, using a constrained tree of several parallel Kalman filters, finds several applications such as locating and tracking aircraft and tracking missiles or satellites from several sensors. Such targets exhibit unpredictable changes in the velocity vector from time to time. A suitable target model must, along with the constant velocity variables, be able to generate changes in the velocity vector, which can be referred to as manoeuvre variables [Ricker and Williams, 1978].

To reduce the number of Kalman filters from M^2 to M, they implement M filters given by the conditional mean $E[\vec{X}_k|\vec{Y}_k]$ for each measurement and use the average manoeuvre variable to initialize the M Kalman filters. The probability $p(\vec{S}_k = \alpha_i|\vec{Y}_k)$ is determine using the Bayes rule to the conditional mean leading to a new filter that computes the estimated state vector from the weighted sum of all the state vectors generated by the individual filters. The state $\vec{S}_k$ is defined as the manoeuvre variables at time $\vec{t}_k$ where $\vec{S}_k = \{\alpha_1, \alpha_2, ..., \alpha_M\}$ is chosen from all possible combinations of the discrete manoeuvre variables, where α_i is one set of values for the manoeuvre variables [Ricker and Williams, 1978].

The new estimate state equation $\hat{X}_{k+1}$ that comes from the best estimate of $\vec{X}_{k+1}$ given that the manoeuvre variable is α_i, the covariance matrix P_{k+1}, the average manoeuvre $\vec{U}_{k+1}$ and the block diagram for the tracking filter are given in [Ricker and Williams, 1978]. These equations are used to truncate the tree structure and limit the number of Kalman filters to M. In the paper they discuss the implementation of the above equations to tracking rapid manoeuvre and they discuss some improvement in track estimate over the familiar extended Kalman filter.

Another method was developed by [Bogler, 1987] for tracking a manoeuvre target using input estimation. This method is used for the case of a one-dimensional acceleration target manoeuvre model. The advantages of this method are used for higher data rate tracking system, low lag time between the manoeuvre initialization and detection, and do not require reinilization of the filter as soon as the manoeuvre is detected. He further develops the CHP method (after [Chan, Hu and Plant, 1979]) to the one-dimensional target acceleration case. He reworked the CHP algorithm into a simple recursive method using the Magill technique discussed above that would provide the best Kalman filter with maximum a posteriori probability so as to detect and correct for the target manoeuvre.

As discussed previously the CHP method proposes that the manoeuvring target's input parameters be estimated in a minimum mean square error (MMSE) sense. If the input parameters (time of manoeuvre and strength of manoeuvre) are estimated correctly, they can be used to calculate the state correction required to account for the prior target manoeuvre [Bogler, 1987].

The simulations for the performance of the CHP algorithm are shown in the paper. The results demonstrate that the CHP method could accurately detect and correct an acceleration discontinuity under a variety of manoeuvre models. A bank of 20 parallel filters was used, each spaced on sampling time apart, T, where each of these filters were reset to zero after 20 sampling times. With this method he shows the rapidity with which the acceleration is first detected after the acceleration step started [Bogler, 1987].

II.2.8.3.3.4 Various Implementations of the Interacting Multiple Model Algorithm

Another interesting method was developed by [Bar-Shalom, Chang and Bloom, 1989]. They show how a set of only two or three filters, operating in the Interacting Multiple Model (IMM), can perform equally or better than the [Bogler, 1987] method using a set of 20 parallel filters, therefore reducing costs of implementation. Their method consists in modelling the manoeuvre as a switching of the state model, where the various state models can be of different dimensions and driven by process noise of different intensities. Then they estimate the state according to the interacting multiple model [Bar-Shalom , Chang and Bloom, 1989].

The IMM algorithm given by [Blom, 1984] for systems with Markovian switching coefficients has been reevaluated by [Blom and Bar-Shalom, 1988]. They derive the IMM algorithm by applying the fixed depth merging approach. The IMM algorithm exploits further evaluation for the timing of hypothesis reduction.

To derive the IMM algorithm [Blom and Bar-Shalom, 1988] assume that the system is to evolve according to one out of r possible linear Gaussian models with jumps between these models according to a Markov chain. They used the total probability theorem to the model posterior probability density function (pdf) of state yielding to $P[\vec{X}_k|M_j(k),\vec{Y}_{k-1}]$ where $M_j(k)$ stands for model j in effect during the period ending at time k. Then they deduced that this equation is a mixture with weightings $\mu_{ij}(k-1|k-1)$ for different model $M_i(k)$. This mixture is assumed to be a combination of Gaussian pdfs and then approximated through moment matched by a single Gaussian. Therefore, by comparison, this equation follows from the linearity of the Kalman filter and shows that the input to the filter matched to model j is obtained from an interaction of the r filters, which consist of the mixing of the estimates $\hat{\vec{X}}(k-1|k-1)$ according to the probabilities $\mu_{ij}(k-1|k-1)$. These steps are equivalent to hypothesis merging at the beginning of the cycle Kalman filtering. This algorithm is illustrated in Figure II.15 where one cycle consists of the following four steps [Blom and Bar-Shalom, 1988] [Bar-Shalom, ch. 2, 1990]:

1. Compute the mixed initial condition of the estimate $\hat{\vec{X}}^{0j}(k-1|k-1)$ for the filter matched to $M_j(k)$ and its corresponding covariance $P^{0j}(k-1|k-1)$. The model match filters are run in parallel for each model.

2. Compute the likelihood functions corresponding to r filters $P[\vec{X}_k|M_j(k), \vec{Y}_{k-1}]$.

3. Find the model probabilities $\mu_j(k)$. The input to each filter at the beginning of the cycle is a mix of their outputs from the previous cycle with suitable weightings that reflect the current probability of each model and the mode transition probabilities.

4. Compute the latest state estimate $\hat{X}(k|k)$ and the covariance equations P(k|k) using the current output probability.

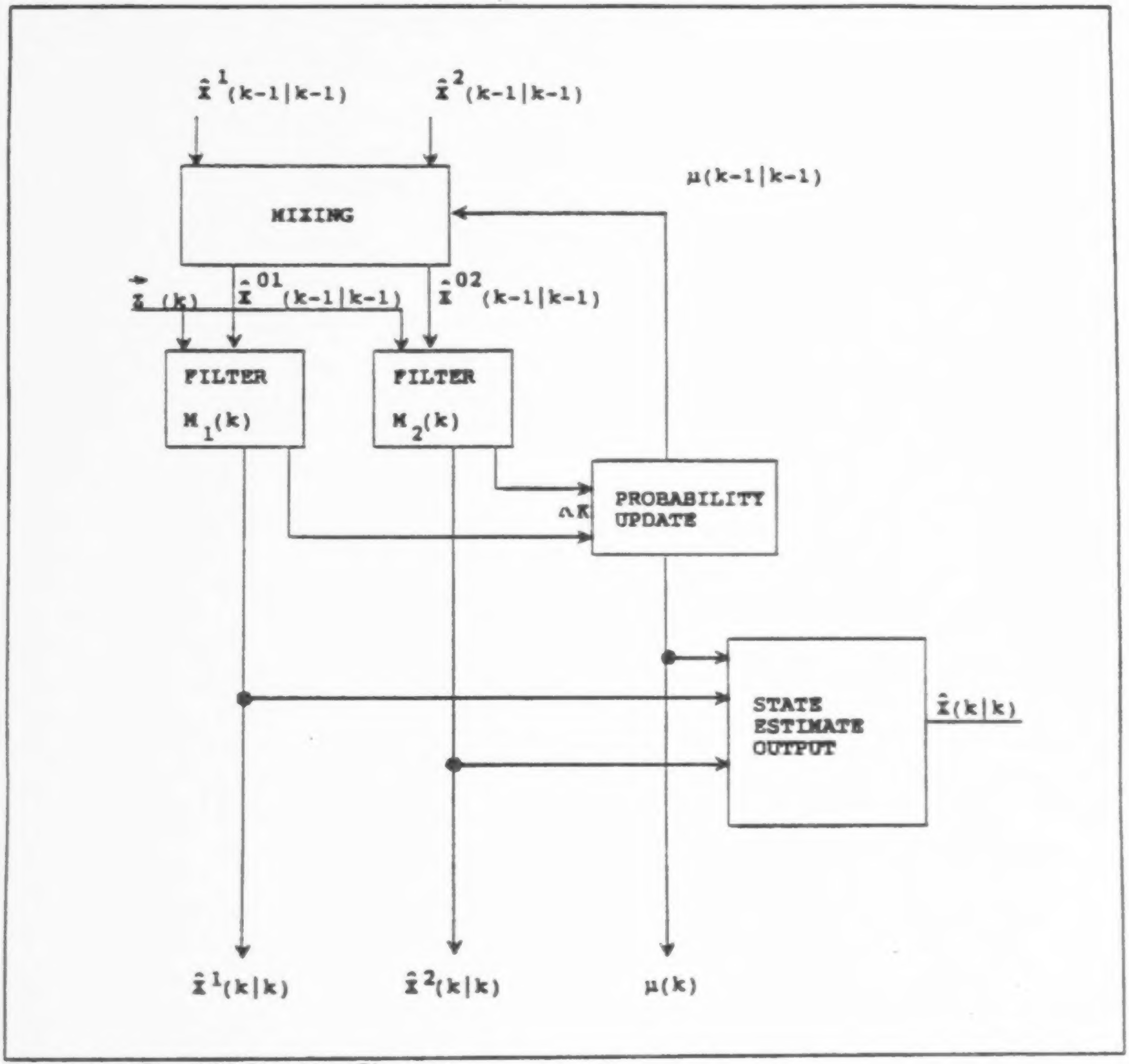
$\hat{x}^1(k-1|k-1)$
$\hat{x}^2(k-1|k-1)$
$\mu(k-1|k-1)$
MIXING
$\vec{z}(k)$
$\hat{x}^{01}(k-1|k-1)$
$\hat{x}^{02}(k-1|k-1)$
FILTER
$M_1(k)$
FILTER
$M_2(k)$
ΛK
PROBABILITY UPDATE
STATE ESTIMATE OUTPUT
$\hat{x}(k|k)$
$\hat{x}^1(k|k)$
$\hat{x}^2(k|k)$
$\mu(k)$

Figure II.15. The IMM Algorithm Diagram

The IMM algorithm was enhanced by [Guu and Wei, 1991]. They propose decorrelation processes to strengthen the IMM algorithm at high measurement frequency to track a manoeuvring target. They suggest this method since high measurement frequency induces correlated measurement noise. With the decorrelation process, they find significant improvement of the system performance especially in velocity and acceleration performance.

[Guu and Wei, 1991] implement the IMM algorithm using a second order model used when the target is non-manoeuvring and/or the use of several third order models for the manoeuvring state with different process noise levels. A third order model filter has a larger process noise to respond to the rapid change of acceleration at the time of manoeuvre. A bank of N Kalman filters is used to operate simultaneously in the IMM algorithm. Each filter corresponds to a model. The probability of the model being correct is evaluated from measurement data and filter output. Then, the weighted sum of all filter outputs with their probabilities being the weighting coefficients is the overall system output [Guu and Wei, 1991] as described in detail by the IMM algorithm above.

The decorrelation process applied to the measurement noise is made by letting the vectors or matrices in equations (II.62) and (II.78) be the i^{th} order model dimension and $\lambda = \exp(-\beta t)$ [Guu and Wei, 1991] be the preset value of noise correlation. Thus, by rederiving the measurement equation, the process noise can be made to be uncorrolated with the new measurement noise. In most practical systems, this procedure can be omitted with little degradation in performance. Therefore the IMM algorithm is applied to the case with correlated measurement noise by substituting $\hat{H}$ for H^i, $\hat{V}_k^i$ for $\vec{V}_k$ for $i = 1, 2, \ldots, n$ and $\vec{Y}_k$ for $\vec{Z}_k$ [Guu and Wei, 1991] where

$$\vec{Z}_{K+1} = \hat{H}_K^i \vec{X}_K + \hat{V}_K^i \qquad \text{(II.120)}$$

in relation with equations (II.62) and (II.78).

In further research [Averbuch, Itzikowitz and Kapon, 1991] compared the IMM algorithm with the Viterbi Algorithm (VA). In the paper presented, they compare the performance of the IMM on the Viterbi algorithms when applied to the problem of radar tracking of a single manoeuvring target.

The IMM algorithm is based on the Bayesian approach and the Viterbi algorithm is based on the minimum a-posteriori probability (MAP) approach. In the Bayesian approach, as explained above, the state vector $\vec{X}_k$ is estimated by an approximation to its conditional mean $E[\vec{X}_k|\vec{Y}_k]$ where $\vec{Y}_k$ is the measurement sequence. In the MAP approach the conditional mean of the system state vector based on a single most probable history (hist) is approximated. The conditional mean (i.e. $E[\vec{X}_k(t)|\text{Hist}(t),$

$Y_k(t)$]) is approximated by using the corresponding extended Kalman filters. Thus, using suboptimal techniques, one attempts to reduce the number of most unprobable histories [Averbuch, Itzikowitz and Kapon, 1991].

The Viterbi algorithm can be summarized as follows. There are N possible models assumed, and until time t there are N histories with maximum likelihood that is tracked. At the beginning of each time step, the VA chooses the N surviving histories out of N^2 possible extensions of the previous histories thus choosing one history with maximal likelihood for each possible current model $M_j(t)$, where j stands between 1 and N. The VA algorithm gives the optimal solution when it is assumed that the pdf of the measurements depends only on the current model to which the system conforms. The VA is quite simple. More details are given in [Averbuch, Itzikowitz and Kapon, 1991].

For a tracking system, the VA does not give the optimal solution history but an approximation of the most probable history since the measurement depends on the target dynamics histories. Thus the VA applied to tracking problems is summarized as follows [Averbuch, Itzikowitz and Kapon, 1991]:

1. For each possible model $M_j(t)$:
    a. For each possible previous model $M_i(t-1)$ compute the probability weight of the history $\{Hist_i(t-1), M_j(t)\}$.
    b. Then compute the surviving history $Hist_j(t)$.
2. Finally compute $\hat{X}_k$.

After the comparison of the IMM and Viterbi algorithms with simulation and results applied to the problem of radar tracking of a manoeuvring target, the authors conclude that their performance depends on the dimentionless parameter η which is the ratio of the maximal difference between the acceleration levels of any two models times the time interval between measurements over the standard deviation of the measurement error. Thus for large η, both algorithms identify decisively the model which is closest to the real acceleration level and provide good acceleration estimate. For small η, neither one is decisive but VA performs better and the IMM algorithm provides better position estimates during the delay period at the beginning of a track and after the start of a manoeuvre [Averbuch, Itzikowitz and Kapon, 1991].

The IMM algorithm has also been used with other techniques to improve tracking of a manoeuvring target. In fact, [Houle and Bar-Shalom, 1989] proposes the integration of multisensor probabilistic data association filter (MSPDAF) and the IMM algorithm. This algorithm (IMM/MSPDAF) is capable of tracking a highly manoeuvring target using measurements from diverse sensors in the presence of a cluttered environment. The IMM algorithm is used for tracking a highly manoeuvring target and the MSPDAF is used for tracking a target in clutter.

The MSPDAF results from the adaptation of the nonparametric probabilistic data association filter (PDAF) with the multisensor (MS) case. The MSPDAF algorithm uses the PDAF for the measurement association and state estimation and sequential updating for the multisensor integration [Houle and Bar-Shalom, 1989]. The PDAF is used for tracking a target in a cluttered environment and was evaluated in [Bar-Shalom and Birmiwal, 1983]. Further readings concerning MSPDAF are given in [Bar-Shalom, 1978; Bar-Shalom and Birmiwal, 1983; Bar-Shalom and Fortmann, 1988]. The IMM/MSPDAF algorithm is given in eight steps and is presented with detail in [Houle and Bar-Shalom, 1989].

The [Houle and Bar-Shalom, 1989] paper presents and compares the results of single model-based filters, of the IMM/MSPDAF algorithm with two models (IMM2) and with three models (IMM3). To simulate the results they present two trajectory cases that could be considered generic for seaskimmers or aircraft operating in evasive mode. The results have shown that the IMM was able to adapt itself to the type of motion exhibited by the target in the presence of heavy clutter thus acceding to high accuracy in the absence of acceleration and keeping the target in track during the high acceleration periods [Houle and Bar-Shalom, 1989].

II.2.8.3.3.5 Multiple Manoeuvring Target Tracking

Another method that remains to be discussed in this section is the problem of multiple manoeuvring target tracking. [Emre and Seo, 1989] uses a global modelling approach to Data Association (DA) and manoeuvre detection and estimation (MDE). Data association and manoeuvre estimation problems were simultaneously solved using system identification techniques for multitarget tracking problems. Their approach to both DA and MDE was to view them as concurrent problems where possible interaction between targets was taken into account. Therefore, manoeuvre detection and estimation techniques used for a single target was then applicable to simultaneously estimating the accelerations and performing data fusion for multitarget tracking [Emre and Seo, 1989].

In order to obtain suboptimal solutions applied to the system identification problem, multiple model adaptive Kalman filtering is used. They propose two suboptimal solutions to reduce computational load associated with multiple model Kalman filtering. The proposed suboptimal solutions are the one step conditional maximum likelihood and maximum a posteriori estimation techniques. These techniques are applied in conjunction with a monitoring scheme which could detect and correct misassociations. They apply the "fault detection techniques" for monitoring, detecting and correcting possible DA errors and simple system identification techniques [Emre and Seo, 1989].

They derive their global model for multitarget tracking where all uncertainties could be described simultaneously using a single mathematical model with unknown time varying problems. They thus suggest that the correct data association corresponds to finding the right sequence of values for the time varying parameter $\Theta(t)$ which allows the permutation of the output equation (II.82) at time t (i.e. $\vec{\mathbf{Y}}_t = [y_1, ..., y_t]$), and by considering an assignment of average values to the accelerations at time t in equation (II.78). An extensive discussion of the mathematical model for multitarget tracking is given in [Emre and Seo, 1989] and other references, and data association has been discussed in section II.2.2.

The general model derived for multi target tracking data association is therefore introduced with the addition of parameter $\Theta(t)$ which is the vector of all uncertainty parameters in equation (II.77) and is thus applied to adaptive multiple Kalman filtering. Hence, the derivation for approximate adaptive filtering is performed and applied to the new adaptive filtering equations in order to limit the number of Kalman filters to be used. The conditional maximum likelihood and the Bayesian estimates are introduced in [Bogler, 1987; Bar-Shalom, Chang and Bloom, 1989] and are extensively derived in [Emre and Seo, 1989] for suboptimal solutions for multiple model adaptive Kalman filtering. Finally, they apply their global model showing the estimated tracks following the actual tracks closely for three different targets on the same plot. They compare the same tracking estimates using both suboptimal techniques which seem to have very similar results [Emre and Seo, 1989].

[Chung, Gustafon and Emre, 1990] bring an extended solution to multiple manoeuvring target tracking using the global method from [Emre and Seo, 1989]. They also incorporate data association that assigns measurements to existing tracks and target manoeuvring problems in a multitarget tracking algorithm. [Chung, Gustafon and Emre, 1990] use the one step conditional maximum likehood technique with extended Kalman filters and an adaptive compensator. To further reduce the computational load, they add a validation matrix in the tracking structure. The validation matrix is used to select the highest possible events considered by tracking filters, therefore selecting the highest probability measurements. Their approach allows the tracking of multiple manoeuvring targets over a wide range of situations [Chung, Gustafon and Emre, 1990].

The algorithm is well described in [Chung, Gustafon and Emre, 1990] and seems to yield good simulated results. For non-linear measurement models, extended Kalman filters were used to estimate the state vector $\hat{\mathbf{X}}(k|k)$ recursively.

The calculation of corresponding likelihood is based on each hypothesis once the measurement data is obtained. The conditional estimate of target state is evaluated and combined with the individual estimate upon each hypothesis weighted by the corresponding likelihood function. Then the target motion path with severe manoeuvre is treated by a new adaptive procedure which is implemented for tracking solutions. A detection criterion for a manoeuvre is utilized, and after the manoeuvre is detected, a compensation algorithm is applied [Chung, Gustafon and Emre, 1990].

The results of the paper show that they are able to track four nonmanoeuvring targets simultaneously with relatively low error in position and velocity. Furthermore, their algorithm is able to track two manoeuvring targets simultaneously, thus showing the performance of their adaptive algorithm [Chung, Gustafson and Emre, 1990].

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ANNEX A

Use or disclosure of data contained on this sheet is subject to the restriction on the title page of this report.

APPENDIX A - Data Fusion Lexicon

Active Sensor	Sensor which detects an object from the echos or the return of its own emitted signal.
Alignment	Processing of filtered or unfiltered target status from sensors to achieve a common time base and a common spatial reference.
Ambiguity Resolution	A decision procedure for eliminating a discrete alternative from consideration after sufficient data has been obtained showing it to be untenable (e.g., resolution of left/right ambiguity of bearing data from a beam formed line array of sensors). The phrase is sometimes used to indicate decisions made between competing association hypotheses.
Angle of Arrival (AOA)	A measure of the direction or propagation of electromagnetic radiation upon arrival at a receiver.
Areas of Interest (AOI)	That area of concern to the commander, including the area of influence, areas adjacent thereto, and extending into enemy territory to the objectives of current or planned operations.
Artificial Intelligence (AI)	A branch of computer science which investigates the theory and technology by which computing machines can be made to perform tasks currently requiring human intelligence. This discipline is interested in the study of mental faculties through the use of computational models based on symbolic processing.
Assessment	A high-level process by which the set of data for all targets (target states and classification) is

	compared (correlated) with previously identified behavioral patterns for all possible situations to describe the status of activities in the surveillance volume.
Assignment	The process by which sensor gathered data is related to an object or objects.
Association	The process of matching kinematic, attribute, or time history data to the appropriate targets to create tracks.
Attributes	As in common usage, state variables (whether discrete or continuous) which describe interesting aspects of the objects being observed and can be related through a sensor model to the actual measurements produced by the sensors (e.g., position, velocity, size, class, type, hull number, equipment numbers, emission frequencies, disposition, allegiance, etc).
Automatic Gridlock	Automatic alignment of units within a grid system requiring a reference unit from which each system computer calculates corrections/compensations based on all mutually held tracks/targets.
Automatic Target Recognition	(also "Non-Cooperative Target Recognition") A specialized form of target tracking featuring a high level of automation. {ATR}
Bayesian Data Associated Algorithm	An association algorithm which introduces explicit prior densities for the track states and association hypotheses and computes the posterior probabilities for tracks and hypotheses by means of Bayes rule. Such an algorithm usually maintains multiple alternative hypotheses, with their scores, and updates them recursively.

Bayesian Probability Theory	A statistical decision theory developed by the Reverend Thomas Bayes (1702-1761) which assumes probabilistic descriptions of the measurement values and prior knowledge to compute a probability value for each hypothesis.
Bearing Line	A line indicating the azimuthal direction of an entity.
Belief	A hypothesis or proposition about some situation. See Measure of Belief.
Blackboard	A globally accessible data used for recording intermediate, partial results of problem-solving. Typically, the blackboard is partitioned to represent hypotheses at different levels of abstraction and mediates the cooperative activities of multiple "subexperts" or specialists.
Chaff	Radar confusion reflectors which consist of thin, narrow metallic strips of various lengths and frequency responses, used to reflect echoes for confusion purposes.
Classification	A determination by any means whereby the category of person, object, or phenomenon is provided (e.g., naval class, country of origin, aircraft type, etc.).
Classifier	1. A computational process which determines the class of an object. 2. A type of measurement from which the class of the object can be directly inferred.
Clutter	Reports of detections which arise from objects not of interest or from sensor anomalies (e.g., clouds, mountains, whales, permanent echoes, etc.)

Combination	The act or process of associating for a common purpose.
Command, Control Information System Architecture	A description of a command and control system in system engineering terms which usually includes: • the various components of the system • the functions which are performed • the structure within which these functions are performed • connectivities with the structure for providing command, coordination, and information flows • interfaces with external entities
Command and Control (C2)	The exercise of authority and direction by a proper designated commander over assigned forces in the accomplishment of a mission. Command and control is supported through an arrangement of personnel, equipment, communications, facilities, and procedures which are employed by a commander in planning, directing, and coordinating and controlling forces and operations in the accomplishment of a mission. The basic functions of command and control are decision making and force/resources management.
Command and Control System	The facilities, equipment, communications, procedures, and personnel essential to a commander for planning, directing, and controlling operations of assigned forces pursuant to the missions assigned.
Composite Track File	The file containing all tracks to which all received sensor data or reports have been allocated.
Conditional Probability	Probability of occurrence of an event restricted to the occurrence of a previous event.

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Contact	1. A set of detections/measurements believed to be associated with a single target. 2. An object detected by one sensor.
Contact-to-Contact Association	Association process between a sensor contact and an MSDF global contact.
Contact-to-Track Association	Association process between a sensor contact and an MSDF global track.
Covariance Matrix	In filtering technique, matrix which contains the variance of each state variable and their mutual covariance.
Cross-Range	Axis perpendicular to the range axis passing trough the target location.
Cueing	A collection asset management technique whereby coarse grain (detection, general location and possible recognition) information obtained from wide area surveillance systems is used to concentrate the efforts of secondary sensor systems with more detailed information gathering capability to obtain fine grain (location, recognition, and possibly identification) information in order to identify the composition of enemy units for decision making purposes and to acquire targets.
Data Association	The process of generating, scoring, and deciding on hypotheses about the question of which detections/measurements under consideration refer to the same object (come from the same target, should be associated) and which refer to different objects. The alternative hypotheses may or may not be explicitly represented if, for example, decisions are made according to heuristic rules.

Data Fusion	A process dealing with the alignment, association, correlation, and combination of data and information from multiple sources to achieve refined position and identity estimation, and complete and timely assessments of situations and threats as well as their significance.
Decision Aid(s)	Tools to enhance human decision-making performance by identifying key factors, structuring the decision process, estimating values, evaluating alternatives, predicting outcomes, effectively presenting information, or effectively managing information.
Decision Rules	In general, a class assignment rule. In classical decision theory, a class assignment or the maximum a-posteriori probability.
Declaration	Conditional probability representing probability of a sensor nominating or declaring a target classification based on observations of a true target or list of targets according to some ranking schemes given sensor has observed a true target (ranking schemes may be simple or probabilistic). If probabilistic, the ranking scheme will be conditional probabilities.
Dempster-Shafer Theory	(also "Belief Functions theory) A theory introduced by Shafer (1976) as an extension to the work of Dempster in probability theory (1967) in which a "frame of discernment" is defined over all the hypotheses of interest.
Dependency	A relation between the antecedents and corresponding consequents produced as a result of applying an inferential rule. Dependencies provide a record of the manner in which decisions are derived from prior data and decisions.

Detection	The discovery by any means of the presence of a person, object, or phenomenon of potential military significance in a particular area under observation.
Direction Finding	A procedure for obtaining bearings of radio frequency emitters with the use of a highly directional antenna and a display unit on an intercept receiver or ancillary equipment.
Dissimilar Source Integration (DSI)	The integration of data from various classes of sensors (radar to ELINT to acoustic). Includes associating classification and identification information to amplify track data.
Doctrine	IF-THEN rules used to implement threat evaluation weapon assignment.
Doppler Radar	A radar system which differentiates between fixed and moving targets by detecting the apparent change in frequency of the reflected wave due to motion of target or the observer.
Electronic Countermeasures	That division of EW involving actions taken to prevent or reduce an enemy's effective use of the electromagnetic spectrum. Electronic countermeasures include electronic jamming and electronic deception.
Emitters	That class of enemy entities detected or classified initially by attributes related to observables depending on emission of electromagnetic radiation by the entity.
Evasive Mode	Applied to missile or aircraft which fly in a way to hide from the sensor coverage envelop of the target.

Event Recognition	The ability to declare that a specific event is occurring or has occurred based on analysis of a series of activities and known factors such as Toe, doctrine, etc.
Expert System(s)	1. A computer system that achieves high levels of performance in task areas that for human beings require years of special education and training. 2. A computer program that embodies the expertise of one or more experts in some limited domain and applies this knowledge to make useful inferences for the user of the system.
Extended Kalman Filter	An algorithm which applies the Kalman filter update equations to nonlinear measurements by linearizing the measurement function about the most recent state estimate.
False Alarm	Sensor report which does not associate with any target because of noise or deception.
Field Of View	A 2-D or 3-D area or volume delimiting the scan space of a sensor. (FOV)
Figure Of Merit	A weighing system for allocating priorities in, for example, algorithm selection in a multi-sensor data fusion system. (FOM)
Filter	An algorithmic entity aimed at improving signal-to-noise discrimination in target detection.
Firm Track	1. An established track. 2. A new (tentative) track becomes a firm track when sufficient update information or other entries are made to raise the confidence level such that the track is considered real or valid.

Fixed Reference Point	A geographical fixed point entered into the system as a standard point for measurement.
Fusion Products	1. Level 1 products are those which specify position, identity, amplifying characteristics/features, movement intentions for a single entity. 2. Level 2 products are those which specify (as above) for multiple/grouped entities, specify relationships among entities, specify tactical intent, and estimate lethality. 3. Level 3 products provide threat assessment and other higher level intelligence functions.
Fuzzy Set Theory	Unlike conventional set theory, which requires binary membership state of the elements of a set, the Fuzzy set theory (1965) developed by Zadeh allows partial membership.
Gate	Interval, ellipse or generally hyper-ellipsoid which surround a contact or a track state vector.
Gauss-Markov Process	Discrete stochastic process of a gaussian random variable in which the probability of occurrence of future states depend only on the present state.
Global Central-Level Track	Same as MSDF Global Track.
Hard Fusion	(also "hard-decision sensor fusion") In a sensor-level fusion architecture, this is the method by which sensors measure signals and make a binary decision, without a measure of uncertainty or confidence, to produce a track declaration for the data fusion processor.
Heuristic Processes	A process or function that maps from problem state descriptions to measures of desirability (usually quantitative).

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Identification	The determination by any means whereby the true character or individuality of a person, object, or phenomena is provided.
Identification Friend or Foe	1. Cooperative IFF - A system of radio interrogation and reply generally used in connection with radar to identify aircraft, ships, or ground elements. 2. Non-cooperative IFF - Identification techniques usually based on high-resolution sensors; techniques which do not rely on cooperation from the target of interest.
Indirect Fusion (Global or Regional Fusion)	The fusion of widely distributed sensors which may look at targets from varying spatial and temporal aspects (e.g., multiple RPVs).
Inferential Rule	An association between antecedent conditions and consequent beliefs that enables the consequent beliefs to be inferred (deducted) from valid antecedent conditions.
Information (Intelligence)	Unevaluated material of every description including that derived from observations, reports, rumors, photographs, and other sources, which when analyzed, produces intelligence.
Initiation	In tracking, the process of establishing a new track in the system.
Integration	The process of combining information from various sources to arrive at a more complete understanding of the tactical situation.
Kalman Filter	A recursive filter that computes the least mean square estimate of an object's state from linear measurements.

Kill Probability	A measure of the probability of destroying a target.
Knowledge	Facts, beliefs, and heuristic rules.
Knowledge Base	The repository of knowledge in a computer system.
Knowledge-based Expert System	A computer system employing human knowledge to solve problems that ordinarily require human intelligence. Such systems simulate expert human performance and present a human-like facade to the user.
Local Tracking	A track held on ownership sensor and tracked by fusion centre. Contract with remote track.
Manoeuvre	An action resulting in the modification of the course of an object in motion.
Maximum Likelihood Estimator (MLE)	A nonrecursive filter which computes the least mean square estimate of a vector parameter based on linear or nonlinear measurements.
Measure of Belief	In the theory of Dempster and Shafer, beliefs are organized into a "frame of discernment" which enumerates all possible beliefs about some event of interest. Each is assigned a number which reflects the amount of evidence available which supports that belief. If a Bayesian prior density available, the measure of belief is assigned to a proposition will be equal to its probability.
Measure Of Effectiveness	A grading system to evaluate the effectiveness of a process. {MOE}
Measurement Matrices	In filtering technique, matrices which link the measurement vector with the state vector.

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MSDF Global Track/Contact	Track/Contact created by (or added to) the MSDF function and residing in the MSDF track database.
Non-Organic Data	Data from sources or sensors outside the organic area of coverage that are usually processed on a non-real-time basis.
Observables	Those state variables of an object which can be estimated from the sensor data, or those attributes of an object which can be deduced from the observations made about it.
Organic Sensor Data	Data from own (i.e, friendly or "blue") sources or sensors detecting tracks within an area of interest.
Over the Horizon Radar	A radar system that makes use of the ionosphere to extend its range of detection beyond line-of-sight. Over-the-horizon radar may be either forward scatter or back-scatter systems.
Passive Sensor	Sensor which detects object directly from the signal (radiation, emission, perturbation, etc) emitted by the target.
Point Defence	Point defence has as its purpose the defence of specified geographical areas, cities, and vital installations. One distinguishing feature of point defence missiles is that their guidance information is received from radars located near their launching sites.
Pop-Up Manoeuvre	Manoeuvre performed near the end of the course of a missile, which has a half circle shaped path and which ends on the target.

Position Correction	The process of updating track position and velocity for a particular track.
Predicate calculus	A positive inference (deduction) characterization system consisting of a language for expressing propositions and of inference rules which allows the "calculation" of the truth of propositions.
Prediction	A process of determining the position a track will occupy when the next sweep of radar comes by, assuming that there are no course and/or speed changes. It enables the tracking program module to automatically move the symbol when no new position information is available and provides a basis for the bifurcation process.
Process Noise	In filtering technique, term in the target model measurement which takes into account source of uncertainty other than measurement.
Radar Coverage	The limits within which objects can be detected by one or more radar stations (note: Radar coverage takes into account aircraft size, altitude, screening angle, site elevation, type radar, antenna radiation pattern, and antenna tilt).
Radar Cross Section	The ratio of the power returned in a radar echo to the power impinging on the target reflecting the signal.
Reference Point	A symbol entered by certain console operators to indicate either a fixed geographic position or a point with a constant position relative to a track.
Resolution	The ability of a system to distinguish between two adjacent objects and to display them separately.

Rule	A pair, composed of an antecedent condition and a consequent proposition, which can support deductive processes.
Rule-based Interference Techniques	Computer programs which explicitly employ rules or rule set components.
Rules of Engagement (ROE)	A predetermined set of directives which govern actions and responses during an encounter involving combat forces.
Scan	A complete list of the detections made by a sensor based on a single look at the environment. Use of the work "scan" often implies a model where the event of detecting any target in the sensor coverage area is independent of the detection of the other targets, and that detections are never split or merged.
Sensor Spatial Resolution	The minimum separation between two objects which allows the sensor to detect the presence of two objects instead of one (e.g., for a bearing sensor, the minimum angular separation between distinguishable objects).
Sensor Status	Current information on a given sensor including location, mode and current tasking.
Sensor Tasking	The process of formally directing a specific sensor(s) to collect information on an area, an entity, an activity, or an event.
Signal	A detectable physical quantity or impulse that conveys information.
Signal-to-Noise Ratio	The ratio of the signal power to the noise power at a particular point in a system. This ratio is often expressed in decibels.

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Situation Abstraction	The construction of a generalized or specialized representation from incomplete sets of data.
Situation Assessment	The process of interpreting and expressing the environment based on Situation Abstraction products and information from technical and doctrinal databases.
Soft Fusion	(also "soft-decision sensor fusion") In a sensor-level fusion architecture, this is the method by which sensors measure signals and make a m-ary decision, with a measure of uncertainty or confidence.
State estimation	(also "target tracking") A component process of data fusion by which an attempt is made at the end of each scan of the sensor to estimate, assuming a dynamic model of behavior, the parameters, such as the position coordinates and velocity components, based upon the sets of new and existing (previous scan) target reports from sensor measurements.
State Vector	In filtering technique, vector which contains the estimated value of each state variable (position, speed, course, etc) of a target.
Surveillance	The systematic observation of aerospace, surface, or subsurface area, places, persons, or things by visual, electronic, photographic or other means.
Surveillance volume	A spatial area in which sensors operate to achieve detection.
Synergism	Circumstance where the resulting effect of a combination of two systems is greater than the sum of each individual effect.

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Tactical Picture	The combination of locational, referential and narrative data into an understanding of the operational environment.
Target	In tracking, the word is often used to refer to any object tracked, whether or not an attack is contemplated.
Target Acquisition	The detection, identification, and location of a target in sufficient detail to permit the effective employment of weapons. Among sensor people, the phrase refers to the first detection of the target by the sensor.
Target Signature	A set of unique sensor signal (measurement) characteristic which is typical of a particular target class and distinguishes the individual target signal from background noise, disclosing its presence and identity.
Target State	Both the kinematic state, established through higher-order derivatives (position), velocity, etc., and behavioral state, such as electronic state, fuel state, etc..
Threat Assessment	A multi-perspective process of interpreting estimates of lethality and risk in terms of the ability of own force to engage the enemy effectively, and indications and warning of enemy intentions by coupling products of Situation Assessment with the information provided by a variety of technical and doctrinal databases.
Threat Evaluation	A multi-perspective (red, white, blue) process of developing estimates of danger, lethality, intent, and risk associated with a set of red and white observations.

Track	To display, record, calculate, or measure the successive portions of a moving object. To establish the path of a target by any method. To follow a target, noting course and speed. The aggregate of information stored, communicated, and displayed as a representation of an object (in space) of tactical significance. Examples include automatic track, auto-eligible track, local track, manual track, master track, remote track, slaved track, vehicular track, EW bearing line, EW fix, EW QR missile track, special points, ASW bearing line, ASW fix.
Track-to-Track Association	Association process between a sensor track and an MSDF global track.
Track Classification	The categorization of a tack into one of a predefined set of meaningful class or division of tracks.
Track Filtering	A computational process by which "best" estimates of the states of an entity are derived from measurements.
Track History	A series of points representing the most recent position updates of a track which may be displayed on a display console at operator request. This aids the console operator in following the path of a manoeuvring track.
Track Initiation	The process of establishing a new track in the system.
Track While Scan	A method of target tracking which allows more than one target to be observed and tracked simultaneously. Systems using this technique do not change their antenna scan when acquiring the target.

Tracking	The computational process dealing with the estimation of an object's true position based on noisy observations (measurements) of it. Tracking may consist of filtering (estimating the position at the time of the latest observation), smoothing (estimating the position at a point in the past), and prediction (estimating the position at a point in the future).
Vulnerabilities	a. Enemy Vulnerability - An enemy vulnerability is any condition or circumstance of the enemy situation of the area of operations which makes the enemy especially liable to damage, deception, or threat. b. National Vulnerabilities - National vulnerabilities are those susceptibilities of a nation to any action, by any means, in peace or war in which its war potential may be reduced or its will to fight diminished.

ACRONYMS

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LIST OF ACRONYMS

AAM	Alignment Accelerometer Module
AAW	Anti-Air Warfare
ACDS	Advanced Combat Direction System
ACS	Afloat Correlation System
ADAM	Automated Data for Aerospace Maintenance
ADM	Advanced Development Model
ADT	Automatic Detection and Tracking
AFCEA	Armed Forces Communications and Electronics Association
AGARD	Advisory Group for Aeronautical Research and Development
AI	Artificial Intelligence
AMEP	Advanced Modular ESM Processor
ANN	Adaptive Neutral Network
AOC	Association of Old Crows
AOR	Operational Support Ship
AP	Associative Processor
AQAP	Allied Quality Assurance Publication
ARM	Anti-Radiation Measures
ARO	Auxiliary Readout
ASDC	Ada Software Development Centre
ASIC	Application Specific Integrated Circuits
ASSM	Anti-Surface Ship Missile
ASST	Anti-Ship Surveillance and Targeting
ASW	Anti-Submarine Warfare
ASWIS	ASW Information System
ATM	Alternative Tracks Method
ATR	Automatic Target Recognition
AUTOLIGN	AUTOmatic sensor aLIGNment
BAM	Bus Access Module
BBUS	BIU Interface
BF	Beam Frequency
BI	Serial Data Bus Interface (module)
BIF	Bearing Intercept Fix
BIU	Bus Interface Unit
BW	Beam Width
C^2	Command and Control
CAD	Computer-Aided Design
CAM	Computer-Aided Manufacturing

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LIST OF ACRONYMS

CPM	Conditional Probability Matrix
CANEWS	CANadian Electronic Warfare System
CASE	Computer-Aided Software Engineering
CB	Common Bus
CC	Cache Controller
CCP	Command and Control Processor
CCRO	Close Control Readout
CCS	Command and Control System
CE	CIO Environment Simulation (module)
CFAR	Constant False Alarm Rate
CG	Cruiser
CGN	Nuclear Powered Cruiser
CHP	[Chan, Hu and Plant]
CI	Loran-C Interface (module)
CIO	Communication Intercept Operations
CISTI	Canada Institute for Scientific and Technical Information
CIWS	Close-In Weapons System
CM	Cache Memory
CO	CIO Interface Simulation (module)
CoP	CoProcessor
COTS	Commercial Off-The-Shelf
CP	Central Processor
CPF	Canadian Patrol Frigate
CPU	Computer Processing Unit
CRAD	Chief Research And Development
CS	Combat System
CS	Common Routines (modules)
CSCI	Computer Software Configuration Item
CSCRS	Cost Schedule Control and Reporting System
CSTSF	Combat System and Test Support Facility
CV	Aircraft Carrier
CVBG	Battle Group Aircraft Carrier
CVN	Nuclear Powered Aircraft Carrier
DA	Data Association
DARO	Data Amplification Readout
DB	Data Base
DBMS	Data Base Management System

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LIST OF ACRONYMS

DD	Distributed Data Management (module)
DDG	Destroyer
DF	Direction Finding
DGMDO	Director General Maritime Doctrine and Operations
DH	Display Handler (module)
DM	Display Management (module)
DMCS	Directorate Maritime Combat System
DMCS-9	Director Maritime Combat Systems (Electronic Warfare)
DMCS-2	Directorate Maritime Combat System (Surface and Air)
DMCS-7	Directorate Maritime Combat System (Combat Systems)
DND	Department National Defence
DNR	Director Naval Requirements
DNR-3	Director Naval Requirements (Combat Systems)
DoD	Department of Defence
DP	Sim Display Support (module)
DPS	Data Processing Set
DR/DSMR	Dynamic System Monitoring and Reconfiguration (module)
DRAM	Dynamic RAM
DRE	Defence Research Establishment
DREA	Defence Research Establishment Atlantic
DREO	Defence Research Establishment Ottawa
DREV	Defence Research Establishment Valcartier
DS	CCS Display Support (module)
DSIS	Director Scientific Information Services
DSN	Distributed Sensor Network
DSS	Department of Supply and Services
DT	SPS-49 Radar Interface (module)
ECC	Eavedrops Cache Controller
ECM	Electronic CounterMeasures
EE	EW Environment Simulation (module)
EH	Error Handler (module)
EHI	European Helicopter Industry
EISG	Electronic Information System Group
ELINT	ELectronic INTelligence
EM	Electronic Warfare (EW) Management (module)
EM	Emission warfare resource Management
EMC	ElectroMagnetic Compatibility

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LIST OF ACRONYMS

EMCON	EMission CONtrol
EMI	Electro Magnetic Interference
EO	Electro Optic
EOT	Electro-Optic Tracker
EP	Enhanced Processor
ERP	Effective Radiated Power
ES	Expert System
ES	Electronic Support Measures (ESM) Interface (module)
ESM	Electronic Support Measures
EW	Electronic Warfare
EWS	Electronic Warfare Supervisor
EWSS	Electronic Warfare Simulation System
FC	Fire Control
FCS	Fire Control System
FFG	Frigate
FLIR	Forward - Looking Infra-Red
FM	File Management (module)
FPB	Fast Patrol Boat
FX	Fusion eXperimental
GDB	Global Data Base
GLSE	Generalized Linear least Squared Estimation
GP	Gyro Processing (module)
GR-UK	Greenland - United Kingdom
GST	Goods and Services Tax
HE	High Explosive
HEA	Horizontal Estimation Architecture
HF	High Frequency
HFE	Human Factors Engineering
hist	history
HVU	High Value Unit
HW	Hardware
I/O	Input/Output
IC	CIO Interface (module)
ID	Identification
ID	Identification (module)
IDS	Interface Design Specification
IEEE	Institute of Electronic and Electrical Engineers

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LIST OF ACRONYMS

IF	IFF Interface Simulation (module)
IFF	Identification Friend or Foe
ILS	Integrated Logistics Support
IMCS	Integrated Machinery Control System
IMM	Interacting Multiple Model
IMU	Internal Measurement Unit
INS	Inertial Navigation System
IOI	Input/Output Interfaces
IOP	Input/Output Processor
IOS	Information from Other Sources
IP	IFF System Interface (module)
IP	Instruction Processor
IPS	Interconnections Per Second
IPU	Information Processing Unit
IR	Infra-Red
IRAD	Internal Research And Development
IRST	Infra-Red Search Track
ISA	Industry Standard Architecture
ISI	Integrated Surveillance Integration
JDL-DFS	Joint Directors of Laboratories - Data Fusion Subpanel
JPDA	Joint Probabilistic Data Association
JPDAF	Joint Probabilistic Data Association and Fusion
JPO	Joint Program Office
KF	Kalman Filter
KBS	Knowledge-Based Systems
km	kilometre
kts	Knots (Nautical)
LAMS	Local Area Missile System
LOS	Line Of Sight
LPI	Low Possibility of Intercept
LRR	Long Range Radar
LTM	Long Term Memory
MA	Memory Array
MAP	Minimum A-posteriori Probability
MBP	Multidimensional Binary Partitions
MD	Multi-Sensor
MDE	Manoeuvre Detection and Estimation

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LIST OF ACRONYMS

MEWPADS	Maritime Electronic Warfare PAyload Development Study
MFR	Multiple(Multi-) Function Radar
MHT	Multiple Hypothesis Tracking
MHTC	Multiple Hypothesis Track Correlation
MI	Memory Interface
MIPS	Million Instructions Per Second
MLE	Maximum Likelihood Estimator
MMI	Man-Machine Interface
MMSE	Minimum Mean Square Error
MOE	Measure Of Effectiveness
MOP	Measures of Performance
MP	Maintenance Processor
MRR	Medium Range Radar
ms	millisecond
MS	Multi-Sensor
MSC	Modified Spherical Coordinate
MSDF	Multiple Sensor Data Fusion
MSDHS	Mission System Data Handling Subsystem
MSE	Mean Square Error
MSI	Multi-Sensor Integration
MSPDAF	Multisensor Probabilistic Data Association Filter
MST	Multi-Sensor Track
MTT	Multiple Target Tracking system
NA	Navigation (module)
NAAWS	NATO Anti-Air Warfare System
NATO	North Atlantic Treaty Organization
NB	Simulation Interface Unit Simulation (module)
NCCS(A)	Naval Command and Control - Afloat
NCNB	Non-Comment Non-Blank
NCTR	Non-Cooperative Target Recognition
ND	Inertial Navigation System (INS) Remote Display Interface (module)
NFR	NATO Frigate Replacement
NG	Inertial/Gyro/Navigator Interface Simulation (module)
NGS	Next Generation SHINPADS
NL	Loran-C Interface Simulation (module)
NLP	Natural Language Processing
nmi	nautical mile

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LIST OF ACRONYMS

NNSF	Nearest-Neighbour Standard Filter
NO	Omega Interface Simulation (module)
NS	Navigation Switchboard Interface (module)
NSA	New Shipborne Aircraft
NTDS	Naval Tactical Display Symbols
NUSC	Naval Underwater Systems Centre
OI	Omega Interface (module)
OMI	Operator-Machine Interface
OP	Operator Panel
OPEVAL	OPerational EVALuation
ops	Operations Per Second
PDA	Probabilistic Data Association
PDAF	Probabilistic Data Association Filter
PDF	Probability Density Functions
PE	Processing Element
PGC	Program Generation Centre
PGCC	Program Generation Control Centre
PH	Peripheral Handler (module)
PIPG	Paramax Information Products Group
PMV	Prime Mission Vehicle
PRF	Pulse Repetition Frequency
PRI/PW	Pulse Repetition Interval/Pulse Width
PTC	Propulsion Training Centre
PW	Pulse Width
QAB	Quick Action Button
QR	Quick Reaction
R&D	Research and Development
RA	SPS-49 ADT Interface Simulation (module)
RAM	Random Access Memory
RC	Radiation Control System Interface Simulation (module)
RCS	Radar Cross Section
RF	Radio Frequency
RFP	Request For Proposal
RFSS	Radar Frequency (RF) Signal Simulator
RMC	Royal Military College
RMF	Reconfigurable Modular Family
RMS	Root Mean Square

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LIST OF ACRONYMS

ROTP	Regular Officer Training Plan
RPV	Remote Piloted Vehicle
RS	SG-150 ADT Interface Simulation (module)
RWR	Radar Warning Receiver
SA	Situation Assessment
SC	Sim System Readiness/Control (module)
SCC	Simulation Control Centre
SDB	Serial Data Bus
SDI	Strategic Defence Initiative
SDX	Standard Distributed Executive (module)
SG	SG-150 Radar Interface (module)
SHINCOM	SHipboard INtegrated COMmunication
SHINMACS	SHipboard INtegrated Machinery Control System
SJSL	St-John Shipbuilding Limited
SL	System Loader (module)
SLCM	Submarine Launched Cruise Missile
SLOC	Source Line Of Code
SM	ESM System Interface Simulation (module)
SM	Sensor allocation/cueing Management
SMI	Serial Maintenance Interface
SN	Scenario Generation (module)
SNAF	Soviet Naval Air Force
SQL	Standard Query Language
SR	CCS System Readiness/Control (module)
SRP	Ship Replacement Program
SS	Conventional Submarine
SSAN	Auxiliary Nuclear Powered Submarine
SSBN	Nuclear Powered Balistic missile-armed Submarine
SSC	Services and Supplies Canada
SSGN	Nuclear Powered Guided missile-armed Submarine
SSKP	Single-Shot Kill Probability
SSN	Nuclear Powered Submarine
SSW	Surface-to-Surface Warfare
STM	Short Term Memory
SW	Software
TACTAS	TACtical Towed-Array Sonar
TDE	Target Data Extractor

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LIST OF ACRONYMS

TEWA	Threat Evaluation and Weapon Assignment
TG	Target Generator (module)
TM	Track Management (module)
TMA	Target Motion Analysis
TS	Tactical Situation
TSA	Tactical Situation Area
TTG	Time-To-Go
TWS	Track-While-Scan
UAV	Unmanned Airborne Vehicles
UCCS	Underwater Command and Control System
UD	Upper Diagonal
UDG	Unisys Defense Group
UDUT	Upper Diagonal Upper Transposed
UHF	Ultra High Frequency
URG	Underway Replenishment Group
USN	United States Navy
VA	minimum a-posteriori probability Viterbi Algorithm
VHF	Very High Frequency
VME	Virtual Memory Extended
VME	Versa Module Eurocard
WARM	WAr Reserved Mode
WBS	Work Breakdown Structure
WP	Warsaw Pact
WW II	World War II

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PARAMAX RESEARCH AND DEVELOPMENT BIBLIOGRAPHY DATABASE

15 June 1992
PARAMAX Systems Canada
Subsidiary of Unisys

DATA FUSION IRAD CASE 92-002

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1. INTRODUCTION

The PARAMAX Research and Development (R&D) department has established a Bibliography Database for recording the results of the collected literature and providing easy search capabilities for literature references for all R&D cases. This Database was developed using dBase IV software.

This document describes the Database structure for the literature survey and how to access and review particular studies using Key Words. The Appendix for each R&D case includes a list of the main "Key Words" selected for the literature and a listing of the literature collected for that project.

2. DATABASE STRUCTURE

The Table 1 shows the Database Structure. A short description for each field is given below:

- The Number indicates the number of the field to be used.
- The Field Name contains all the topics to be used in the Database.
- The Field Type is a defined character type.
- The Width of each field name is given; it allows the maximum number of characters that can be entered in the field.

The Field Name indicates the following information provided for each study:

- The "title" field contains the title of the study.
- The "authors" name field contains the name of the author(s) associated with the title study.
- The "type" field indicates if the document is an article, a book, a conference paper, a report or presentation materials.
- The "class" field represents the security level of the document, i.e., secret, classified or unclassified.
- The "source" and the "year" indicate where and when the document was published.
- The "subject" field indicates the topic discussed.
- The "comment" field is a brief summary of the document content.
- The "project" field indicates for which projects the entry is pertinent.

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TABLE 1

Number	Field Name	Field Type	Width
1	TITLE	Character	100
2	AUTHORS	Character	50
3	CLASS	Character	20
4	TYPE	Character	12
5	YEAR	Character	12
6	SOURCE	Character	100
7	SUBJECT	Character	40
8	COMMENT	Character	200
9	PROJECT	Character	6

3. KEY WORDS

The main Key Words for search in the Database are given in the Appendix for the particular project. They are sorted in alphabetical order. A subset of these generic Key Words are given to enhance the search capability.

4. FILTER IN A FIELD

The Filter in a Field allows one to get all records from specific key words and fields chosen. For example, suppose one wants to filter all the records with the key words "association" and "alignment" from the "subject" and "comment" fields respectively. From the dot prompt, type the following:

```
.SET FILTER TO LIKE ("*ASSOCIATION*", SUBJECT) .OR. LIKE ("*ALIGNMENT*",
 COMMENT)
```

and press "ENTER". Then type BROW and press "ENTER". All records having these key words from the specified fields will be shown on the screen. This can also be done for other key words in other fields.

5. PRINT REPORT

The records from the Database can be easily printed by using the "Print Menu". The Appendices give a print out report for each project.

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6. BIBLIOGRAPHY REPORT

The Bibliography Report of all entries is given below.

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APPENDIX A

INVESTIGATIONS ON TARGET TRACKING AND CLASSIFICATION USING MULTIPLE SENSOR DATA FUSION

PARAMAX-SSC Contract number:
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A.1 KEY WORDS

The main Key Words for searching in the Database are given in appendix B for the particular project. They are sorted in alphabetical order. A subset of these generic Key Words are also given. For example, under the Key Word "ALIGNMENT" is found "DATA ALIGNMENT", another Key word. Also the Key Word "MULTITARGET" can be used as "MULTI-TARGET" for a search. How to search in the Database as will be explained shortly. The Key Words for search in the Database must be typed in capital letters.

ALIGNMENT - DATA ALIGNMENT
MISALIGNMENT
SPATIAL ALIGNMENT
TIME ALIGNMENT

ARCHITECTURE - COMPUTER ARCHITECTURE
DISTRIBUTED ARCHITECTURE OR PROCESSOR
FUSION ARCHITECTURE

ASSOCIATION - DATA ASSOCIATION
JOINT PROBABILITY DATA ASSOCIATION OR JPDA

BENCHMARK ALGORITHM

COORDINATES - POLAR COORDINATES
CARTESIAN COORDINATES

CORRELATION - CORRELATED NOISE
TIME CORRELATION

DATA - DATA ALIGNMENT
DATA ASSOCIATION
DATA FUSION

ESTIMATION - ATTRIBUTE ESTIMATION
STATE ESTIMATION

FILTER - FILTERING
KALMAN FILTER
ADAPTIVE FILTER

HUMAN FACTOR

INTELLIGENCE - ARTIFICIAL INTELLIGENCE OR AI

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MILITARY SYSTEM OR MISSION		
MULTIPLE HYPOTHESIS TRACKING OR MHT		
NEUTRAL NETWORK		
SENSOR	-	MULTISENSOR INFRARED SENSOR
SYSTEM	-	EXPERT SYSTEM
TARGET AND TRACKING	-	TARGET MANOEUVRE TARGET MODEL TARGET TRACKING TRACKING ALGORITHM TRACKING MULTITARGET MULTITARGET TRACKING TRACKING TARGET
THEORY	-	DECISION THEORY EVIDENCE THEORY BAYESIAN DEMPSTER-SHAFER FUZZY LOGIC

A.2 MSDF BIBLIOGRAPHY

The following pages contain a summary of the MSDF Bibliography. This MSDF Bibliography report contains the Author name, the year of publication, the subject and the type of document and its source.

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